Essays in Labour Economics

Federica De Pace

A thesis submitted to the School of Economics and Finance
in partial fulfillment of the requirements of
the Degree of Doctor of Philosophy

QUEEN MARY UNIVERSITY OF LONDON

London, March 2020

Declaration

I, Federica De Pace , confirm that the research included within this thesis is my own work or that where it has been carried out in collaboration with, or supported by others, that this is duly acknowledged below and my contribution indicated. Previously published material is also acknowledged below.

I attest that I have exercised reasonable care to ensure that the work is original, and does not to the best of my knowledge break any UK law, infringe any third party's copyright or other Intellectual Property Right, or contain any confidential material.

I accept that the College has the right to use plagiarism detection software to check the electronic version of the thesis.

I confirm that this thesis has not been previously submitted for the award of a degree by this or any other university.

Signature: Federica De Pace
Date: 27 March 2020

Details of collaboration and publications The work presented in Chapter 3 is based on a joint work with Prof. Alessandra Bonfiglioli. I carried out the data work and most of the drafting, while data interpretation was equally contributed by both the authors.

Acknowledgements

This thesis could not have been written without the encouragement and support of a number of people.

First, I am deeply grateful to my supervisor, Giulio Fella, for being present with inestimable dedication during every step of my PhD. His supervision has been for me the key to start and pursue this journey. I owe him basically everything I have learnt as a researcher. I am also very thankful to Alessandra Bonfiglioli, my second supervisor, for being extremely supportive in time of great need. I also owe her teaching me how to co-work on a project, which has turned out to be a lot of fun. Her multi-tasking ability is and will be extremely inspiring to me.

I also thank all the participants to the Macroeconomics reading group at Queen Mary, in particular Gino Gancia, Anna Raute, Tatsuro Senga and Roman Sustek, for their precious advice. This dissertation has been greatly enriched through my interactions with them.

I am also very grateful to the people who I met along the way and supported me, both academically and personally. In particular I want to thank Divya, for being my point of reference during this journey. Her academic but mostly moral support has been precious. Thanks to Divya, together with Mimosa, Michele and Julen, also for having immediately become my family in London. I want to thank Carlos for his admirable patience in guiding me through my first steps with Julia. I thank Fulvia for the great encouragement and, with Alessio, Edoardo, and Soledad, for being my “safe space” at work. Thanks to Veronica with whom I have started this endeavour. I am also very grateful to Bénédicte, Bertil and Clara, who have made my move to Paris much smoother and gave me warmth outside my comfort zone.

A special thanks is for my family. Your sacrifices, love and unconditional support have allowed me to live this incredible experience with you always on my side.

Finally, this thesis is dedicated to Xavier. You have been my source of optimism, enthusiasm and balance every single step of the way.

Abstract

This thesis studies two important aspects of labour market earnings dynamics: the post-displacement earning losses experienced by high-tenure workers, and the evolution of the gender wage gap within firms linked to export activity.

The first two essays aim at understanding and quantifying the forces behind the post-displacement earning losses observed in the data. I first introduce the main empirical and theoretical works in the literature. Then, I propose a structural model of the labour market with on the job search, in which firms are heterogeneous in productivity and workers accumulate both general and specific skills while employed. Jobs are destroyed at an endogenous rate due to idiosyncratic productivity shocks and workers' skills depreciate during unemployment. The model is estimated via simulated method of moments using matched employer-employee data on Germany. By matching moments related to workers' mobility and wage dynamics, the model reproduces the size and persistence of the earning losses observed in the data. The key driver of the post-displacement earning losses is the interaction between the loss in specific (mostly) and general human capital and endogenous separation.

Finally, the third essay studies the effect of firms' export activity on the gender wage gap among its workers. Using matched employer-employee data from Germany for the period between 1993 and 2007, we show that an increase in a firm's export widens the wage gap between male and female blue collar workers, while it reduces it between male and female white collars. In particular, the former effect is stronger for workers in routine manual tasks, while the latter is driven by employees performing interactive tasks. This evidence is consistent with the hypothesis that serving foreign markets relies more on interpersonal skills, which reinforces female comparative advantage and reduces (widens) the gender wage gap in white (blue) collar occupations.

Contents

Declaration **2**

Acknowledgements **3**

Abstract **4**

Introduction **9**

1 The Consequences of Job Loss in the Economic Literature **12**

1.1 Introduction 12

1.2 Empirical Evidence on the Post-Displacement Earning Losses 13

1.2.1 Methodology 13

1.2.2 Earning Losses Decomposition 15

1.3 The Sources of the Cost of Job Loss 16

1.3.1 Job Ladder and Endogenous Separation 18

1.3.2 The Role of Human Capital 19

1.4 Conclusions 26

1.5 Figures 28

References 30

2 Job Ladder, Human Capital and the Cost of Job Loss **32**

2.1 Introduction 32

2.2 The Model 37

2.2.1 Ingredients 37

2.2.2 Workers Mobility and Bargaining Protocol 39

2.2.3 Value Functions 42

2.2.4 Model Mechanisms 46

2.3 Quantitative Analysis 47

2.3.1 Data Description and Sample Selection 47

2.3.2 Model Implementation 48

2.3.3 Calibration and Identification Stategy 50

2.3.4 Model Fit 54

2.4 The Cost of Job Loss 58

2.4.1 Reduced Form Analysis 58
2.4.2 Model versus Data 59
2.4.3 Structural Decomposition of Wage Losses 60
2.5 Conclusions 61
2.6 Figures 64
2.7 Tables 70
Appendices 73
2.A Numerical Details 73
2.A.1 Model Solution Details 73
2.A.2 Optimization Details 73
2.B Data Work Details 74
2.B.1 Construction of the Monthly Panel 74
2.B.2 Variables Definition 75
2.B.3 Construction of the Yearly Panel 75
2.C Unobserved Firm Heterogeneity 75
References 78

3 Export, Female Comparative Advantage and the Gender Wage Gap **80**
3.1 Introduction 80
3.2 Data Description 84
3.2.1 Estimation Sample 85
3.2.2 Descriptive Statistics 86
3.3 Export and Gender Wage Gap: Empirical Evidence 88
3.3.1 The Baseline Estimation Strategy 88
3.3.2 Heterogeneous Effects by Occupation 91
3.4 Export and the Gender Wage Gap: Exploring the Mechanisms . . . 96
3.4.1 Export and Firms' Labour Demand 97
3.4.2 Export and Promotions 99
3.4.3 Export, Gender Wage Gap and Occupational Task Content . 101
3.5 Robustness Checks 105
3.6 Conclusions 107
3.7 Figures 109
3.8 Tables 110
Tables 110
Appendices 123
3.A Classification of Sectors of Activity 123
3.B Task Content of Occupations 125
3.C Export and Gender Wage Gap: Additional Specifications 127

References 131

List of Figures

1.1 Earning Losses in Expansion and Recession. 28
1.2 Earning Losses Decomposition in German IAB data. 28
1.3 Earning, Wage and Employment Losses in PSID data 29

2.1 Timing of events: Unemployed Workers 64
2.2 Timing of events: Employed Workers 64
2.3 Returns to Experience in the SIAB-7514 dataset 65
2.4 Returns to Tenure and Experience: Model VS Data 66
2.5 Post-displacement earning and wage losses in the SIAB-7514 dataset 67
2.6 Post-Displacement Losses: Model VS Data 68
2.7 Wage Losses Decomposition 69
2.C.1 Change in k-means fit with number of clusters 77

3.1 Average Percentage of Exporting Firms by Sector in West Germany, 1993-2007 109
3.2 Average Percentage of Female Workers by Sector in West Germany, 1993-2007 109

List of Tables

2.1 Model Parameters 70
2.2 Targeted Moments 71
2.3 Calibrated Parameters 72

3.1 Firm Export Activity in West Germany, 1993-2007 110
3.2 Exporters vs Non-Exporters Characteristics by Gender 110
3.3 GWG and Exports: All Sample 111
3.4 GWG and Exports: Blue Collar vs White Collar 112
3.5 GWG and Exports: The differential Effect on Blue and White Collar Workers 113

3.6 Firm Demand 114
3.7 Hiring Patterns 114
3.8 Firm Demand and Export Dynamics 115
3.9 Hiring Patterns and Export Dynamics 115
3.10 Promotions 116
3.11 Robustness Checks: Promotions 117
3.12 Occupations by Task Content 117
3.13 Export and Gender Wage Gap by Task Intensity: White Collar, Analytic and Interactive Jobs 118
3.14 Export and Gender Wage Gap by Task Intensity: Blue Collar, Manual and Interactive Jobs 119
3.15 Robustness Checks: Wage Censoring 120
3.16 Robustness Checks: Gender Wage Gap and Export Dynamics . . 121
3.17 Robustness Checks: Gender Wage Gap and Export for High Tenure Workers 122
3.A.1 Sector of Activity (NACE Rev. 2) 123
3.B.1 Tasks and Occupation Classification 126
3.B.2 Tasks and Occupation Classification 126
3.C.1 Export Share and Gender Wage Gap: Other Specifications 129
3.C.2 Export Share and Gender Wage Gap for Blue and White Collar Workers: Other Specifications 130

Introduction

This thesis combines three essays that explore two important aspects of labour market earnings dynamics. It first focuses on one important source of earning risks, specifically the post-displacement earning losses experienced by high-tenure workers. Then, it looks at the evolution of the gender wage gap within firms and, in particular, at its links to firms' export activity.

Both topics are investigated empirically, using a rich administrative matched employer-employee panel dataset on Germany, provided by Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB). The nature of this dataset is crucial to understand the sources of individual earnings dynamics. By reporting complete individuals' labour market histories, as well as detailed information on workers and firms, it allows to separately identify the contribution of both individuals' and firms' characteristics, and to isolate them from the role of search frictions which prevent similar workers from finding equally productive job matches.

Workers and firms characteristics, together with search frictions, are in fact relevant for both the topics covered in this thesis. In the case of post-displacement earning losses for high-tenure workers, the literature suggests that the main driving forces are the loss of a productive and secure job and the loss of workers (general) skills. As for the evolution of gender wage gap, the recent literature has put forward several explanations to this phenomenon, including sorting into different type of firms for male and female workers, the presence of search frictions in the labour market that prevent female workers from finding equally productive matches as their male colleagues, as well as differences in productivity and bargaining power (Card, Cardoso, and Kline, 2015).

In light of these considerations, I devote the first two chapters to the investigation of the role played by search frictions and their interaction with workers' human capital accumulation in the explanation of post-displacement earning losses experienced by high-tenure workers.

In Chapter 1, I provide a survey of some of the main empirical and theoretical works that focus on this topic. The empirical literature shows that workers that experience displacement suffer from very high and persistent earning losses.

For example, Davis and von Wachter (2011) estimate that in the United States displaced male workers with more than three years of tenure suffer losses equal to 12% of the present value of earnings in the absence of displacement. The main recent works in the theoretical literature have stressed the role of the *job ladder* and search frictions for the qualitative explanation of these earnings losses. The job ladder captures the idea that jobs are heterogeneous in productivity and that it takes time for workers to find the most productive jobs. Therefore, it helps explaining the slow recovery in earnings after displacement as unemployed workers enter relatively poorer employment relationships and search for better matches while employed. However, given the high frequency of job-to-job transitions in the data, the job ladder alone is not able to explain the observed persistence of post-displacement earning losses. Therefore, additional forces have been considered. For example, the observed increase in job separation rates at re-employment for displaced high-tenure workers hints at the importance of losses in job security (some examples are the works of Jarosch, 2015; Krolikowski, 2017 and Jung and Khun, 2018). Additionally, the fact that most of the persistence of earning losses is due to the sluggish recovery of wages (rather than employment), stresses the importance of workers' decrease in productivity upon displacement (Jarosch, 2015; Burdett, Carrillo-Tudela and Coles, 2020).

Starting form these observations, in Chapter 2 I propose a general framework to account for the causes of post-displacement earning losses. Specifically, I build and estimate a quantitative, structural search model of the labour market with the following elements: heterogeneous firms, on-the-job search, specific and general human capital accumulation and endogenous job loss. The model is estimated by simulated method of moments using matched employer-employee data on Germany, and by matching moments related to both workers' mobility and wage dynamics, it is able to reproduce the size and persistence of the earning losses observed in the data. The key contribution of this work is that it provides a measurement framework to account for the relative contribution of the drivers of the post-displacement losses. It does so by including specific and general human capital accumulation in a model of job search and by pinning down the relevant parameters using returns to tenure and experience in the data. The results of the counterfacutal analysis show that the key driver of the post-displacement earning losses is the loss in specific (mostly) and general human capital and its interaction with the mechanism of endogenous separation. More precisely, by transitioning into unemployment, high-tenure displaced workers lose a good job and specific human capital. The time spent in unemployment makes them more likely to accept lower productivity jobs, which are less stable because less likely to survive negative productivity shocks. This increases their probability of falling again into unemployment and prevents them to rebuild the lost specific and general skills, slowing down the earnings recovery.

Chapter 3, co-authored with Alessandra Bonfiglioli, studies a different aspect of individual earnings dynamics. It looks at the effect of firms' export activity on the gender wage gap among its workers. In spite of the growing attention on the role of globalisation in widening income inequality, and on the persistence of wage differentials between men and women, this theme has received little attention in the literature so far. We contribute to filling this gap by investigating the role of firms' export activity on the gender wage gap, using matched employer-employee data on Germany for the 1993-2007 period. The structure of the dataset allows us to observe the changes throughout time in export sales of a single firm and the evolution of wages of all the workers employed by that specific firm. We exploit this feature of the data to only focus on variation within worker-firm matches, which allows to look at the changes in relative wages of a female-male pair of workers as the firm expands its export activity. This specification is likely to reveal the causal effect of export on the gender wage gap because it takes into account the possible sources of bias related to individual and firm characteristics, sorting of workers in particular firms and reverse causality issues: it is in fact unlikely that any single worker may affect firm's sales abroad. Our results show that an increase in a firm's export widens the wage gap between male and female blue collar workers, while it reduces it between male and female white collars. In particular, the former effect is stronger for workers in routine manual tasks, while the latter is driven by employees performing interactive tasks. Additionally, this result is robust also to controlling for firm's sales, whose effect on the gender wage gap is quite muted relative to that of export. The fact that the gender wage gap reacts more to export than domestic sales suggests that selling to foreign markets may require the firm to change the intensity in the use of certain skills in a way that makes women relatively more demanded in non-production tasks. This is in line with the existing evidence that women tend to have a comparative advantage in performing white collar tasks, especially those intensive in interpersonal relations and in the use of computers, while they have a disadvantage in blue collar, "brawn"-intensive occupations (see for example Spitz-Oener, 2006; Black and Spitz-Oener, 2010; Borghans, Weel and Weinberg, 2014; Ngai and Petrongolo, 2017; Cortes, Jaimovich and Siu, 2018). If export requires a more intensive use of "male" skills in production (e.g., because it changes the production line in a way that calls for more "brawn"), and of "female" skills in non- production tasks (e.g., because it takes more ability in interpersonal relations to deal with foreign customers), an expansion in foreign activities will increase (decrease) the demand for females in white-collar (blue-collar) occupations and their wages.

Chapter 1

The Consequences of Job Loss in the Economic Literature

1.1 Introduction

Numerous studies have documented the large negative impact of job loss events on several aspects of individuals' life. Workers that experience layoff are confronted with worse labour market outcomes, e.g. lower re-employment opportunities and productivity losses, reduced consumption and health conditions (see Gruber, 1997; Sullivan and Wachter, 2009; Davis and Wachter, 2011, among others).

In particular, most of the works in the labour economics literature show that displaced workers with at least three years of job tenure experience severe losses in earnings, that persist for over twenty years after the event. Furthermore, there is consensus about the fact that the bulk of the earning losses is explained by a reduction in workers' re-employment probabilities, while their persistence is attributed to a stagnant growth in workers' re-employment wages.

Building on these stylised facts, researchers have looked at the possible causes of the post-displacement earning losses. The main theoretical channels highlighted so far have been *i*) the loss of a productive match, *ii*) the loss of a secure job, and *iii*) the drop in workers' productivity, mostly in terms of general skills.

This chapter is dedicated to reviewing and discussing the main contributions in this field. Specifically, Section 1.2 surveys the literature that focuses on the quantification and causal estimation of the post-displacement earning losses, and on the empirical decomposition in employment and wage losses. Section 1.3 covers the most recent works that propose theoretical mechanisms for the explanation of the observed post-displacement earning losses. Section 1.4 concludes.

1.2 Empirical Evidence on the Post-Displacement Earning Losses

The modern literature on the cost of job loss goes back to the early 1990s, when Jacobson, LaLonde, and Sullivan (1993) first documented the presence of large and long-lasting earning losses following job displacement events. The paper contributed significantly to the literature, both in terms of empirical methodology and data used for the estimation. It is, in fact, the first paper to develop the event-study approach still used today to analyse the consequences of a layoff on workers' current and future earnings. It is also the first empirical work in which administrative worker-level data are combined with firm-level data on employment flows. This enabled the authors to identify workers' separations due to mass layoff events and use them as exogenous events in the context of a quasi-natural experimental analysis.[1]

1.2.1 Methodology

The empirical framework developed in Jacobson, LaLonde, and Sullivan (1993) is motivated by the challenge of estimating the causal earning losses suffered by displaced workers. Specifically, they define earning losses as the "*difference between the workers' actual and expected earnings had the event that led to their displacement not occurred*". This definition formally translates into:

$$E(y_{it}|D_{i,s} = 1, I_{i,s-p}) - E(y_{it}|D_{i,s} = 0, I_{i,s-p}) \tag{1.1}$$

where, y_{it} represents earnings of worker i at time t, $D_{i,s}$ is a dummy variable equal to 1 if individual i is displaced at time s and 0 otherwise, and $I_{i,s-p}$ represents the information set on individual i, p periods before separation.

This definition comes with the empirical challenge of approximating the term $E(y_{it}|D_{i,s} = 0, I_{i,s-p})$, which represents the counterfactual expected earnings at time t of individual i displaced at time s in case the displacement event had not occurred and, as such, is not directly observable in the data. Jacobson, LaLonde, and Sullivan (1993) tackle this issue by comparing the average earnings of two groups of workers selected only among male, prime age, high-tenure workers employed in Pennsylvania during the late 1970s and 1980s: a treatment group of workers displaced in a mass layoff event and a control group of continuously

[1] A separation due to a mass layoff event is defined as a separation from a firm (with at least 50 employees) that in the year of displacement experiences a decline in employment at least equal to 30% of its maximum level of employment.

employed workers. Assigning to the treatment group only workers that experience separation for exogenous reasons helps mitigate any bias due to individual selection and uncover the causal effect of job loss on workers' earnings.

In practice this approach is implemented by estimating the following difference-in-difference regression model:

$$y_{it} = \alpha_i + \gamma_t + \beta X_{it} + \sum_{k \geq -m} \delta_k D_{it}^k + \varepsilon_{it} \tag{1.2}$$

where y_{it} represents the real annual earnings for individual i at time t; α_i is an individual fixed effect that absorbs workers' heterogeneity and γ_t represents a year fixed effect. The vector X_{it} is a quadratic polynomial in age for individual i at time t, and D_{it}^k are dummy variables indicating if the worker was displaced due to a mass layoff $k = (-m, -m+1, ..., 1, 2...)$ year before or after t. The estimated coefficients $\hat{\delta_k}$ capture the difference in earnings between the treated and control groups k periods after separation.

Applying this methodology, Jacobson, LaLonde, and Sullivan (1993) document that high-tenure workers who were laid off in 1979 from firms in distress suffered earning losses equal to 40% of their pre-displacement earnings during the displacement year, and 25% six years after separation.

External Validity One of the main concerns about the work by Jacobson, LaLonde, and Sullivan (1993) is about the external validity of the study. This was first raised by Couch and Placzek (2010) who, by applying the same methodology on data on workers in the state of Connecticut in years 1993-2004, estimated much smaller earning losses. The different economic conditions of the two states seemed to matter significantly for the difference in the results of the two papers. In 1980 and 1982, Pennsylvania was in fact hit by two important recessions, that likely affected the recovery of post-displacement workers' earnings, while Connecticut was growing at stable rates and exhibiting much lower unemployment rates in 1993-2004.

Davis and Wachter (2011) confirm the importance of the economic conditions in the determination of the size and persistence of post-displacement earning losses by estimating them separately for periods of recession and expansion for workers employed in the United States in the 1974-2008 period.[2] Their results are in line with Jacobson, LaLonde, and Sullivan (1993) for displacement events occurring in

[2]Periods of recession are identified as years in which national unemployment rate is below 6%, while periods of expansion are considered as years in which the national unemployment rate is above 8%.

recession years and with Couch and Placzek (2010) for workers displaced during times of favourable economic conditions (see Figure 1.1).

The size and persistence of earning losses suffered by high-tenure workers can be affected not only by economic conditions but also by the specific institutions and social security systems. To this effect Schmieder, Wachter, and Bender (2010) and, more recently, Schmieder, Wachter, and Heining (2018) study whether workers in countries with more generous social security systems and less income inequality, like Germany, show significant differences in post-displacement earning losses in comparison to workers in the United States.

Both studies are based on German administrative employer-employee data with the difference that the first paper focuses only on workers displaced in recession years 1981-1985 and follows them from 1975 to 2005, while the second one focuses on a longer time span ranging from 1975 to 2014 and includes displacement events occurring both in recession and expansion years. The conclusions are that German workers suffer from earning losses similar in magnitude and persistence to those suffered by workers in the United States. Additionally, Schmieder, Wachter, and Heining (2018) confirm the findings in Davis and Wachter (2011) and document pro-cyclical earning losses, which are double in size when displacement occurs in periods of recession relative to expansion. This further reveals important similarities with the previous research on the United States.

Large and long lasting earning losses similar in size to the ones discussed above have been also documented for other countries, such as Portugal (Portugal and Carneiro, 2006) and the UK (Hijzen, Upward, and Wright, 2010). This highlights that job loss episodes have sizeable lifelong consequences on workers' earnings independently on the countries' institutions, and understanding their sources is important for designing appropriate labour market policies.

1.2.2 Earning Losses Decomposition

An important starting point to understand what drives large and persistent earning losses is to account for the relative contribution of employment and wages. This has been done by Schmieder, Wachter, and Heining (2018) for Germany, due to the rich information provided in matched employer-employee data, that include both daily wages and days of work.

The authors show that working days drop by almost 25% in the year of displacement, but show a much faster recovery compared to earnings in the following years, almost reaching the pre-displacement levels after ten years. Contrastingly, wages never reach their pre-displacement values, remaining about 8% below their counterfactual path fifteen years after displacement (see Figure

1.2). Therefore, the reduction in employment opportunities after job loss events seems to explain most of the size of the initial earning losses, while the sluggish recovery of re-employment wages appears to be responsible for the persistence of the earning losses.

A similar decomposition has been conducted by Huckfeldt (2018) using PSID data on workers employed in the United States. Qualitatively, the findings are close to those of Schmieder, Wachter, and Heining (2018), with post-displacement wages being accountable for the persistence of earnings. However, quantitatively, the decomposition shows substantial differences in the recovery of employment between the two countries. While employment in the United States fully recovers after two years, it shows much higher persistence in the German data (see Figure 1.3).

These empirical findings represent a crucial starting point for a deeper understanding of the drivers of the post-displacement earning losses. In countries like Germany, where the reduction in employment seems to play an important role in the overall cost of job loss, a focus on mechanisms slowing down re-employment in the years that follow a layoff event seems necessary. For countries more similar to the United States, where workers recovery in working hours is fully reached in two years, a closer look at the sources of workers' losses in productivity at re-employment seems more relevant.

Several papers have investigated the theoretical channels driving the post-displacement earning losses by applying structural estimation techniques that allows to quantify the relative contribution of each of the considered sources. The next subsections are dedicated to describe the main contributions in the field.

1.3 The Sources of the Cost of Job Loss

Models of the labour market with search frictions and on-the-job search à la Burdett and Mortensen (1998), in which workers climb a job ladder in wages (or firm productivity), with higher rungs reached with experience, provide a suitable framework to study the causes of the cost of job loss.[3]

In this framework, both unemployed and employed workers can engage in on-the-job search activity and receive offers infrequently as a result of random sampling from a wage (or firm) productivity distribution. Unemployed workers

[3] The standard version of Burdett and Mortensen (1998) model does not consider heterogeneity in firm productivity, but it has been extended to include it to match better the data on wage distribution.

accept wage offers that represent an improvement upon the unemployment status, while employed workers accept to switch job only if it entails a higher payoff. This implies that newly employed workers (hired from unemployment) are more likely to occupy the lowest rungs of the job ladder, while (long-term) employed workers are positioned on the higher rungs of the ladder and receive higher wages, having accumulated search capital during the course of their career.[4]

Therefore, through the lens of this model, high-tenure workers that experience a displacement event will most likely lose a well paid job at the top of the ladder and, by transitioning into unemployment, will have to restart the search activity from the bottom. It follows that, at re-employment, these workers receive lower wages compared to their high-tenure colleagues that have not been displaced. This mechanism can explain the presence of substantial post-displacement earning losses, whose size depends on the job offer distribution and whose persistence on the frequency of job offers sampling process.

This explains why qualitatively the job ladder model represents a natural framework to justify the observed post-displacement earning losses. However, when matched to the data on workers' mobility, it only predicts transitory post-displacement earning losses. More precisely, given the high frequency of job-to-job transitions observed in most countries, the activity of on-the-job search implies a strong mean-reverting process for wages and, taken on its own, fails to mimic the persistence of job displacement earning losses.

Starting from this observation, the recent literature has extended the basic job ladder framework to take into account several additional mechanisms that help slowing down the recovery in earnings. Some of the most relevant contributions in this field have included the dimension of job stability to the job ladder, either exogenously (Jarosch, 2015) or endogenously in the spirit of Mortensen and Pissarides (1994) (Krolikowski, 2017; Jung and Kuhn, 2018), to make the bottom of the job ladder more "slippery" and the top more stable, as well as skill accumulation during employment and skill loss during unemployment as in Ljungqvist and Sargent (1998) to create an additional channel of persistence (Jarosch, 2015; Huckfeldt, 2018; Burdett, Carrillo-Tudela, and Coles, 2020).

[4]Notice that this model is able to account for returns to experience and tenure observed in the data. In fact, experience is seen as accumulation of search capital that allows workers to climb up the ladder and accept better offers with higher wages. Tenure is interpreted as a sign of a good match that pays high wages and survives counter-offers from other firms, preventing workers from quitting for a better opportunity.

1.3.1 Job Ladder and Endogenous Separation

In Krolikowski (2017) the recovery in workers' post-displacement earnings is lower as the job ladder becomes harder to climb after a transition into unemployment. Specifically, his work takes inspiration from the empirical observation that unemployment spells are serially correlated, that is workers that come out of unemployment face a high probability of losing their job again. To rationalize this stylized fact, Krolikowski (2017) writes a structural model of the labour market with on-the-job search, heterogeneity in match productivity and idiosyncratic productivity shocks modelled as in Mortensen and Pissarides (1994) which deliver endogenous separation.

In this model, workers sample job offers during unemployment and employment from an exogenous distribution of match productivity $F_y(y)$, that generates a job ladder which workers climb over the course of their career. When the match is formed, the realization y of $F_y(y)$ becomes the fixed component of the match productivity, which stays constant over time. Additionally, in each period every match can be hit by an idiosyncratic productivity shocks with realization x drawn from the exogenous distribution $F_x(x)$. Each match is then characterised by a productivity value which is a function of the fixed component y and the stochastic component x, specifically $f(xy) = xy$.

Featuring a stochastic component in the match productivity delivers endogenous transitions into unemployment. When the realization x is negative enough to make the match no longer productive, firm and worker consider more profitable to destroy it and, respectively, to shut down and go back into unemployment. This mechanism generates repeated unemployment spells, since matches with lower fixed component y (likely to originate from unemployment) are more frequently destroyed after a bad realization of x. It follows that when a high-tenure worker (at the top of the ladder) gets displaced, he or she loses both a good and well paid job and a stable match. This additional loss in job stability that follows displacement slows down the process of climbing the ladder and helps increasing the persistence of earning losses.

By matching moments related to workers' separation rates profile by tenure, the model does a good job in replicating the pattern of post-displacement earning losses computed in Davis and Wachter (2011) for the Unites States using PSID data. However, it counterfactually generates too persistent employment losses, which give rise to large and persistent gaps between earning and wage losses. The reason is that the job ladder model with endogenous separation, by generating repeated job loss episodes, mainly acts through the employment margin of the losses and contradicts the decomposition results that documents a very fast recovery of working hours in the Unites States (Huckfeldt, 2018).

In spite of this, the model still underestimates the persistence of the earning losses compared to the data. Specifically, it predicts annual earnings losses of around 40% in the year of displacement, in line with what Davis and Wachter (2011) estimate for periods of recession. However, after ten years the model generates earning losses of around 8%, which is lower than the 18% estimated in for period of recession and the 10% in expansion. This confirms that the job ladder induces a strong mean-reverting process for wages that cannot fully account for the high persistence of post-displacement earning losses, even when the channel of endogenous separation is taken into account.

1.3.2 The Role of Human Capital

In Jung and Kuhn (2018) the persistence of post-displacement earning losses is achieved by considering a life cycle model with a job ladder, endogenous separations and workers' human capital accumulation.[5] The authors stress that in order to replicate the high persistence of earning losses, the model has to be able to reproduce the substantial heterogeneity in both job stability and separation rates observed in the data. Specifically, they highlight two strong sources of heterogeneity in job stability and separation rates among workers in the CPS data for the United States. The first one is induced by workers' age, with older workers on average being less likely to switch jobs and to transition into unemployment. The second one is captured by workers' tenure, with high-tenure workers being employed in more stable matches. These two sources of heterogeneity imply that workers in the same age group can exhibit very different separation rates and, vice-versa, that workers with the same tenure (e.g. zero tenure) exhibit declining separation rates with age. For example, from the authors' calculation on CPS data it results that on average fifty years old workers separate from their firm with probability equal to 2% per month. If transition rates were uniform among this group of workers, the average tenure would be roughly equal to four years. However, their average tenure in the data is eleven years. This implies that the economy is characterised by a significant share of workers that separate from their firm (within the same cohort), but also by a large share of workers in very stable matches, that contributes to push up the average tenure in the aggregated data.

The job ladder and skill accumulation represent the two main tools that deliver this heterogeneity. As in Krolikowski (2017), the job ladder with endogenous separation helps justifying the declining profile of transition rates by tenure. It

[5]In this section I use the term human capital and skills interchangeably.

triggers a selection mechanism such that better matches last longer, given their higher probability of surviving both adverse productivity shocks and poaching of workers by other firms. Additionally, the accumulation of skills over the course of the career makes older workers more productive and less likely to separate after negative productivity shocks, independently on their tenure. These two forces, selection and skill accumulation, generate very stable jobs at the top of the ladder, where matches are more productive and workers are older.

Notice that in this model with endogenous separation, workers' skills are non neutral with respect to separation. This is due to the specific assumption of non full transferability of workers' skills into unemployment, which is modelled considering unemployment income as a fixed amount, independent from workers' pre-displacement accumulated skills.

The model implies that, when high-tenure workers lose their job they lose a particularly good job at the top of the ladder, even if the activity of on-the-job search allows them to eventually reach the average job in the economy, convergence does not happen because jobs at the top of the ladder are characterised by very high stability and very high wages. In other words, the mean reversion mechanism from the bottom triggered by search does not compensate the lack of mean reversion from the top due to high job stability.

Through this mechanism, this model is able to reproduce the large and persistent earning losses observed in the data for U.S. workers. Additionally, by running counterfactual simulations, Jung and Kuhn (2018) show that the selection mechanism induced by the job ladder plays the biggest role (85%) in the explanation of post-displacement wage losses. Workers' skills, on the other hand, play a marginal role.

In this work, the separate identification of the contribution of the job ladder and human capital strongly relies on the assumption of independence of unemployment income from workers' pre-displacement accumulated skills. As explained above, in a model of endogenous separation, this assumption implies that workers' skills are non neutral with respect to separation and therefore allows the identification of the skill process by matching the separation-age profile for workers with the same tenure in the data. This creates two issues. First, the assumption contradicts the fact that unemployment benefits are linked to workers' pre-displacement wages. Second, it implicitly assigns a connotation of firm specificity to the human capital accumulation process, which is challenging to identify in absence of matched employer-employee data. As workers lose both a good firm and human capital upon transitioning into unemployment, it is not feasible to separately identifying the two channels without information on the pre-displacement employing firm.

The two main works that rely on matched employer-employee data to identify the forces behind the cost of job loss and consider general fully transferable human capital are Jarosch (2015) and Burdett, Carrillo-Tudela, and Coles (2020).[6] The first stresses the role of losses in job stability paired with skill decay during unemployment for displaced workers, while the second highlight the importance of the forgone general human capital after displacement events.

Jarosch (2015) starts from the observation that job separations into unemployment are serially correlated and that jobs differ in terms of stability in addition to productivity. To account this empirical fact, he extends a model for the labour market with on-the-job search and matching of outside offers à la Cahuc, Postel-Vinay, and Robin (2006), to include job heterogeneity in both productivity and job security. He allows more productive jobs to be also more stable for exogenous reasons. This creates a job ladder in both dimensions of productivity and stability, which workers climb during their career via job-to-job transitions to eventually reach more stable and productive positions.

Modelling a job ladder in both productivity and job security implies that when workers are displaced involuntary they are set back to the bottom of the ladder, where jobs are less productive and less paid, but also less stable, leading to repeated job loss episodes. This generates more persistence in earning losses by slowing down the recovery of the employment component of the losses in the first years after displacement. This channel seems to be particularly appropriate for Germany which, as opposed to the United States, where employment completely recover almost after two years from displacement, registers slow employment convergence.

The employment component of the losses, however, recovers much faster than earnings, revealing that wages are responsible for most of the persistence in the earning losses even in Germany. In light of this evidence, Jarosch (2015) augments the model to allow for general human capital accumulation in the style of Ljungqvist and Sargent (1998). This additional channel is crucial to capture the slow recovery of wages after displacement.[7] Specifically, during employment,

[6] A third important example is Huckfeldt (2018) who, however, mostly focuses on the cyclicality of post-displacement earning losses in the United States. He attributes the more sever earning losses observed in periods of recession to the higher workers' occupation mismatch rates recorded in these times, which lead to slower accumulation of general human capital.

[7] Jarosch (2015) also considers the sequential auction wage setting mechanism of Cahuc, Postel-Vinay, and Robin (2006). This implies that during the activity of job shopping, if workers decide to quit the current employer to join a more productive firm, they can use the value of the old match as a benchmark to negotiate the new wage. Therefore, by climbing up the ladder, they not only gain better positions, but also build up negotiation rents. This mechanism creates persistence in post-displacement wage losses, since after a lay-off workers lose negotiation rents, more than just a good job. The counterfactual simulation shows, however, that this channel

workers stochastically gain general human capital, which is fully transferable to other firms and to unemployment. However, during unemployment, workers' general human capital can depreciate with a certain probability. The general human capital channel can increase the persistence of post-displacement wage losses through two margins: 1) the direct depreciation of general human capital due to the transition into unemployment for displaced workers (in the treatment group), which is reflected into lower workers' re-employment wages, and 2) the increase in general human capital of non-displaced workers (in the counterfactual group) during employment, which widens the wage differentials between the two groups after displacement. The relative importance of the two margins is an empirical matter, and depends on the estimation of the general human capital accumulation process.

Jarosch (2015) estimates the general human capital accumulation process by targeting the relation between initial re-employment wages (after unemployment) and the length of unemployment spell in the data. This directly informs about the parameter governing decumulation rate of human capital during unemployment. The rate of accumulation of general human capital during employment is, however, derived indirectly by imposing the following equilibrium condition, which ensures that unemployed workers lose human capital as often as employed workers accumulate it:

$$(1-\psi_e)^{u/(1-u)} = (1-\psi_u) \tag{1.3}$$

where u represents the unemployment rate, ψ_u the rate of decay of human capital during unemployment and ψ_e the accumulation rate of general human capital during employment.

The estimated parameters imply a yearly accumulation rate of general human capital of roughly 2% and a yearly rate of skill loss during unemployment of roughly 23%. This implies that the decumulation of general human capital during unemployment is responsible for most of the sluggish post-displacement wage growth, explaining 52% of the present discounted value of post-displacement wage losses.

The importance of human capital for the explanation of the high persistence of long term earning and wage losses is also highlighted in Burdett, Carrillo-Tudela, and Coles (2020). As Jarosch (2015), Burdett, Carrillo-Tudela, and Coles (2020) use German matched employer-employee data to estimate a model of on-the-job search, accumulation of general human capital during employment and skill loss during unemployment to identify the causes of the cost of job loss. However,

only accounts for a small portion of the present value of post-displacement earning losses.

in contrast with the papers discussed so far, they assume an exogenous and homogeneous separation rate along the job ladder and hence don't take into account the job stability channel which delivers serially correlated unemployment spells for workers hired from unemployment. They mostly focus on job ladder and human capital process to explain the cost of job loss.

The model is based on the framework developed in Burdett and Coles (2003), which considers on-the-job search and optimal wage contracting with risk averse agents, and it's extended to consider workers' skill accumulation. The assumption of on-the-job search implies that workers quit for better paid jobs, so firms design optimal wage contracts with backloading of wages in order to reduce quitting incentives. This implies that optimal wages grow with workers' tenure and also that the slope of wage-tenure profile is firm specific, since high-paying firms, by facing less competition, are less in need to link wages to tenure. The wage-experience profile is explained by job shopping and learning-by-doing: employed workers can receive job offers and move to more productive firms which pay higher wages, and accumulate skills every period at a constant rate that increase their productivity and translate into higher wages.

According to this model, high-tenure workers suffer from significant earning losses after displacement because of 1) the loss of a well paid job (represented in this case by a good contract), 2) general human capital depreciation during unemployment, and 3) the lack of general human capital accumulation during unemployment in comparison with non-displaced workers, who instead keep accumulating it while employed.

The quantification of the relative contribution of this three channels is obtained empirically. Specifically, matched employer-employee data help quantifying the role of job ladder, by allowing the estimation of the firm-specific wage-tenure profile. The wage-experience profile over the course of workers' career is used to obtain information on the process of general human capital accumulation during employment while, as in Jarosch (2015), the slope of the re-employment wage-unemployment length relation gives information on the decumulation of workers' general human capital during unemployment. The estimated parameters imply a rate of accumulation of general human capital during employment equal to 4.5% per year, and a rate of skill decay during unemployment equal to 1.7% per year.[8]

[8]Burdett, Carrillo-Tudela, and Coles (2020) calibrate their model for three different groups of workers, classified according to their education level. They find an accumulation rate of general human capital equal to of 4.9% for low educated workers, 4.1% for medium educated workers and 4.8% for high educated workers. The decumulation rate is equal to 1.7% for workers with medium and high education, and 1.2% for those with low education.

The estimation results imply that forgone skill accumulation during unemployment plays the biggest role in explaining the persistence of post-displacement earning losses. Specifically, the fact that individuals in the counterfactual group of non-displaced workers keep accumulating skills at a constant rate, while workers in the treated group do not, can explain roughly 80% of the present discounted value of the earning losses.[9]

It is interesting to notice that both works of Jarosch (2015) and Burdett, Carrillo-Tudela, and Coles (2020) are able to match the size and persistence of the post-displacement earning losses experienced by German workers, while attributing them to different mechanisms. In Burdett, Carrillo-Tudela, and Coles (2020), constant accumulation rates of human capital for workers in the control group, paired with long permanence into unemployment for workers in the treatment group, prevents the convergence of wages after displacement. In Jarosch (2015), when high-tenure displaced workers fall off the ladder, they lose job security and experience repeated unemployment spells which, given the high depreciation rate of skills during unemployment, hinder wages and earnings recovery.[10]

The difference in the role given to general human capital in both papers highlights that the choice of modelling separations and the implied estimation strategy significantly matters. As explained above, the identification strategy of Burdett, Carrillo-Tudela, and Coles (2020) is in fact mainly based on targeting moments related to wage dynamics, such as workers' (firm-specific) returns to tenure and returns to experience. In contrast, Jarosch (2015) focuses on the heterogeneity of job stability along the job ladder, and consequently mostly targets moments related to workers' separation rates into unemployment by tenure, to mimic the serial correlation of unemployment spells observed in the data. The estimation of the parameters governing the evolution of human capital accumulation during employment is indirect and obtained through the equilibrium condition reported in equation (1.3).

Both strategies have shortcomings. In Jarosch (2015) the effect of general human capital on wages is ignored in spite of a vast amount of literature that explains the wage-experience profile observed in the data with theories of human

[9]Burdett, Carrillo-Tudela, and Coles, 2020 estimate the model separately for low and middle skill workers to identify which channel is more important for each category. They find that forgone skills accumulation is still the main source of earning losses for both type of workers.

[10]The different lengths of the unemployment spells in the two papers is given by the choice of different targets to estimate the parameters governing the exit rate from unemployment. Jarosch (2015) uses the unemployment rate, which is equal to 9% in the period considered, delivering a average unemployment spells of 11 months. Burdett, Carrillo-Tudela, and Coles (2020) uses the average non employment-employment rate, which includes all the episodes that are different from regular full-time employment spells, and is equal to 4.5%, which implies average non-employment spells of roughly 22 months.

capital accumulation (see for example Topel, 1990; Dustmann and Meghir, 2005; Lazear, 2009; Yamaguchi, 2010; Altonji, Jr., and Vidangos, 2013; Bagger, Fontaine, Postel-Vinay, and Robin, 2014, among others). Ignoring returns to experience in a model with general human capital accumulation may provide distorted estimates of the accumulation and decumulation process. In fact, both rates of general human capital accumulation during employment and decumulation during unemployment play a role in the reduced form estimation of the returns to labour market (actual) experience. The first plays a direct role: the longer is the workers' actual experience, the higher the accumulated skills, which translate into higher wages. The second plays an indirect role: labour market actual experience is correlated with labour market potential experience, which includes periods of unemployment. The loss of human capital during unemployment reduces workers' re-employment productivity and wages, negatively affecting the estimated returns to actual experience. Therefore workers' wage-experience profile represents an important feature of the data that gives relevant information on the human capital process.

Burdett, Carrillo-Tudela, and Coles (2020) acknowledge this and obtain information on the general human capital process using the observed returns to experience in the data, in addition to the relation between re-employment wages and length of unemployment spell. As mentioned above, by matching returns to experience in the data on average equal to 4% per year, they calibrate a yearly accumulation rate of general human capital equal to 4.5% and a depreciation rate equal to 1.7%, which are respectively twice higher and more than ten times lower than those calibrated in Jarosch (2015).

However, the returns to experience estimated in Burdett, Carrillo-Tudela, and Coles (2020) are higher than those documented in the literature. For example, using the same matched employer-employee dataset on German workers, Dustmann and Meghir (2005) find that skilled workers' wages grow by 6% in the first years of work and decline to 1.2% after five years of experience and unskilled workers' wages grow by 8.2% in the first years of work and become zero after three years of experience.[11]

The estimation of high returns to experience in Burdett, Carrillo-Tudela, and Coles (2020) translates into high accumulation rates of general human capital which, paired with the assumption of constant accumulation rates, entails the

[11]The difference in the estimation in the two works is due to the fact that Burdett, Carrillo-Tudela, and Coles (2020) compute returns to experience without taking into account the possible biases arising from workers' tenure and firms' productivity (e.g. firms' fixed effects), while Dustmann and Meghir (2005) use a control function approach and focus on displaced workers only to isolate the effect of experience.

risk of overestimating the role of general human capital accumulation in the explanation of post-displacement earning losses. This is particularly relevant in this context since post-displacement earning losses are computed on high-tenure workers which, as Dustmann and Meghir (2005) show, exhibit even lower returns to experience (equal to 1.2% and 0 for skilled and unskilled workers with more than five and three years of experience, respectively).

1.4 Conclusions

The goal of this chapter has been to review the main contributions to the literature on the long term consequences of job loss events. The empirical literature provides an established framework to causally estimate the post-displacement earning losses. Additionally, the empirical decomposition of the earning losses into employment and wages provides supporting guidance for the correct understanding of the possible mechanisms that could possibly drive them in countries with different institutional settings. It hints at the fact that in countries like the United States, where the rate of convergence of post-displacement employment is fast, the persistence of earning losses may be more attributable to losses in productivity, while in countries like Germany, where some persistence in employment losses is also observed, job security could also play a significant role.

The main works in the theoretical and structural literature have highlighted the importance of the job ladder in the qualitative explanation of the earnings recovery path after displacement. For the quantitative explanation of the earning and wage losses, some papers have stressed the role of job security, as well as the importance of human capital accumulation during employment and of skills depreciation during unemployment.

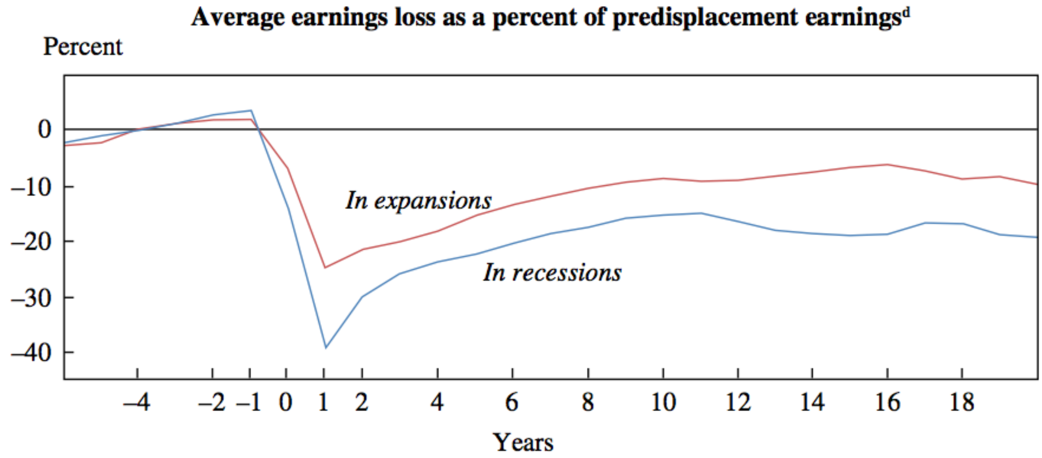
This review shows the presence of an important gap in the literature. The works analysed so far are in fact able to explain the post-displacement earning and wage losses by either taking into account the changes in job separation rates after job loss events for high-tenure workers (see for example Jarosch, 2015; Krolikowski, 2017) or by matching wage dynamics, such as returns to experience (Burdett, Carrillo-Tudela, and Coles, 2020). However, both set of moments represent key stylized facts of the data that can be explained by heterogeneity in separation rates along the job ladder and human capital evolution, which are both likely to play an important role in the persistence of earning losses.

Therefore, a framework that considers both these channels and is able to match moments on separations and wage dynamics - in line with the features of the sample of workers used to estimate the post-displacement earning losses - would help clarify their relative quantitative importance in explaining this stylized fact.

In light of these considerations, the work presented in the next chapter makes a step forward in this literature and represents an attempt to reconcile the works on the cost of job loss with those on earning dynamics.

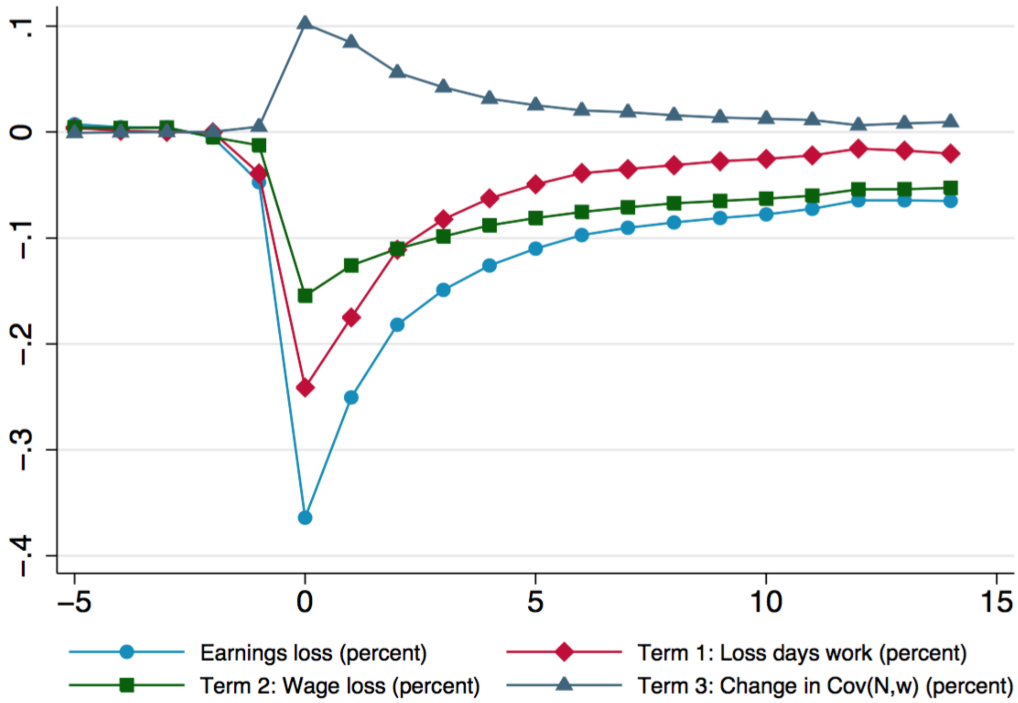
1.5 Figures

Figure 1.1 – Earning Losses in Expansion and Recession.



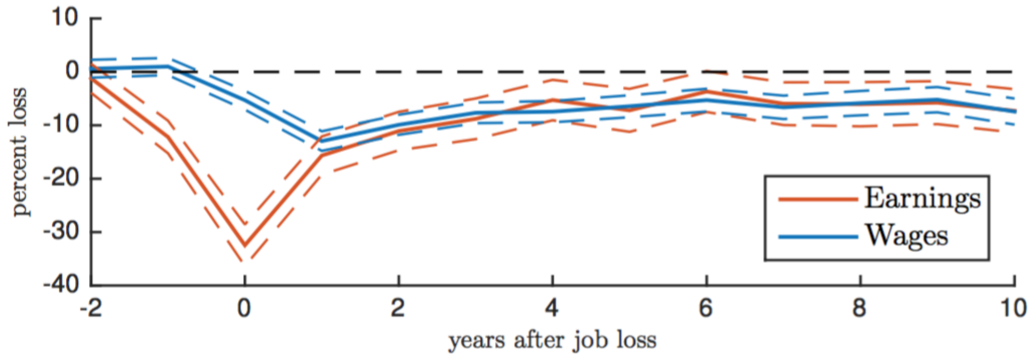
Source: Davis and Wachter, 2011

Figure 1.2 – Earning Losses Decomposition in German IAB data.

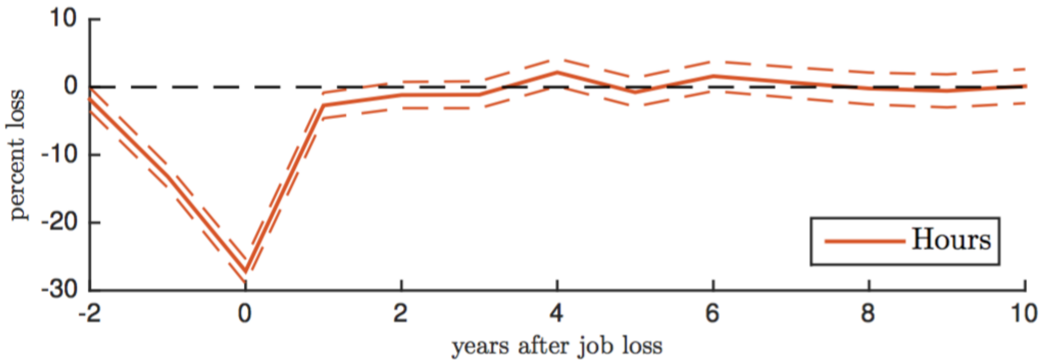


Source: Schmieder, Wachter, and Heining, 2018

Figure 1.3 – Earning, Wage and Employment Losses in PSID data



(a) Wages



(b) Employment

Source: Huckfeldt, 2018

References

Altonji, Joseph G., Anthony A. Smith Jr., and Ivan Vidangos (2013). “Modeling Earnings Dynamics”. In: *Econometrica* 81.4, pp. 1395–1454.

Bagger, Jesper, François Fontaine, Fabien Postel-Vinay, and Jean-Marc Robin (2014). “Tenure, Experience, Human Capital, and Wages: A Tractable Equilibrium Search Model of Wage Dynamics”. In: *American Economic Review* 104.6, pp. 1551–96.

Burdett, Ken, Carlos Carrillo-Tudela, and Melvyn Coles (2020). “The Cost of Job Loss”. In: *The Review of Economic Studies, forthcoming.*

Burdett, Ken and Melvyn Coles (2003). “Equilibrium Wage-Tenure Contracts”. In: *Econometrica* 71.5, pp. 1377–1404.

Burdett, Kenneth and Dale Mortensen (1998). “Wage Differentials, Employer Size, and Unemployment”. In: *International Economic Review* 39.2, pp. 257–73.

Cahuc, Pierre, Fabien Postel-Vinay, and Jean-Marc Robin (2006). “Wage Bargaining with On-the-Job Search: Theory and Evidence”. In: *Econometrica* 74.2, pp. 323–364.

Couch, Kenneth A. and Dana W. Placzek (2010). “Earnings Losses of Displaced Workers Revisited”. In: *The American Economic Review* 100.1, pp. 572–589.

Davis, Steven J and Till M von Wachter (2011). “Recessions and the Cost of Job Loss”. In: *Brookings Papers on Economic Activity* 43.2, pp. 1–72.

Dustmann, Christian and Costas Meghir (2005). “Wages, Experience and Seniority”. In: *The Review of Economic Studies* 72.1, pp. 77–108.

Gruber, Jonathan (1997). “The Consumption Smoothing Benefits of Unemployment Insurance”. In: *The American Economic Review* 87.1, pp. 192–205.

Hijzen, Alexander, Richard Upward, and Peter W. Wright (2010). “The Income Losses of Displaced Workers”. In: *The Journal of Human Resources* 45.1, pp. 243–269.

Huckfeldt, Christopher (2018). *Understanding the Scarring Effect of Recessions.* 2018 Meeting Papers 1207. Society for Economic Dynamics.

Jacobson, Louis S., Robert J. LaLonde, and Daniel G. Sullivan (1993). “Earnings Losses of Displaced Workers”. In: *The American Economic Review* 83.4, pp. 685–709.

Jarosch, Gregor (2015). *Searching for Job Security and the Consequences of Job Loss.* Mimeo. University of Chicago, USA.

Jung, Philip and Moritz Kuhn (2018). “Earnings Losses and Labor Mobility Over the Life Cycle”. In: *Journal of the European Economic Association* 17.3, pp. 678–724.

Krolikowski, Pawel (2017). "Job Ladders and Earnings of Displaced Workers". In: *American Economic Journal: Macroeconomics* 9.2, pp. 1–31.

Lazear, Edward P. (2009). "Firm-Specific Human Capital: A Skill-Weights Approach". In: *Journal of Political Economy* 117.5, pp. 914–940.

Ljungqvist, Lars and Thomas Sargent (1998). "The European Unemployment Dilemma". In: *Journal of Political Economy* 106.3, pp. 514–550.

Mortensen, Dale and Christopher A. Pissarides (1994). "Job Creation and Job Destruction in the Theory of Unemployment". In: *Review of Economic Studies* 61.3, pp. 397–415.

Portugal, Pedro and Anabela Carneiro (2006). *Earnings Losses of Displaced Workers: Evidence from a Matched Employer-Employee Data Set*. Working Papers w200614. Banco de Portugal, Economics and Research Department.

Schmieder, Johannes F., Till von Wachter, and Stefan Bender (2010). *The long-term impact of job displacement in Germany during the 1982 recession on earnings, income, and employment*. IAB Discussion Paper 201001. Institute for Employment Research, Nuremberg, Germany.

Schmieder, Johannes F., Till von Wachter, and Joerg Heining (2018). *The Costs of Job Displacement over the Business Cycle and Its Sources: Evidence from Germany*. Mimeo. Institute for Employment Research, Nuremberg, Germany.

Sullivan, Daniel and Till von Wachter (2009). "Job Displacement and Mortality: An Analysis Using Administrative Data". In: *The Quarterly Journal of Economics* 124.3, pp. 1265–1306.

Topel, Robert (1990). "Specific capital and unemployment: Measuring the costs and consequences of job loss". In: *Carnegie-Rochester Conference Series on Public Policy* 33.1, pp. 181–214.

Yamaguchi, Shintaro (2010). "Job Search, Bargaining, and Wage Dynamics". In: *Journal of Labor Economics* 28.3, pp. 595–631.

Chapter 2

Job Ladder, Human Capital and the Cost of Job Loss

2.1 Introduction

A vast amount of empirical evidence has documented the presence of large and persistent earnings losses following a job displacement (i.e. involuntary job loss) event for high-tenure workers. For example, Davis and Wachter (2011) estimate that in the United States displaced male workers with more than three years of tenure experience losses equal to 12% of the present value of earnings in the absence of displacement. Schmieder, Wachter, and Heining (2018) estimate even larger losses of 15% for Germany.

Workhorse search models of the labour market with search frictions, on-the-job search and firm heterogeneity imply that earnings losses just reflect the loss of a good job (see, for example Burdett and Mortensen, 1998; Postel-Vinay and Robin, 2002). These models feature a *job ladder* that workers climb over the course of their career, which captures the idea that it takes time to find a suitable job. Specifically, unemployed workers have lower reservation productivity and therefore start their career by accepting less productive and lower paying jobs. Once employed, they can reach better positions that pay higher wages through the activity of on-the-job search. Therefore the positive association between employment tenure and wages (and therefore post-displacement earnings losses) just reflects the fact that workers search among heterogeneous jobs until they settle in high productivity jobs that both pay more and last longer.

An alternative view with a long tradition in labour economics is that the positive association between tenure and earnings losses reflects the accumulation of skills that are productive (and therefore reflected in wages) only with the current but not future employers (firm-specific human capital) (see, for example Topel, 1990; Lazear, 2009). In this framework, earnings losses reflect the loss of the firm-specific skills accumulated during the job spell. Additionally, if workers' general skills increase during employment and deteriorate during the time spent in unemployment (as for example in Ljungqvist and Sargent, 1998), earning losses can mirror the workers' losses in general human capital accumulated while employed.

This work provides a framework that encompasses these three mechanisms to quantify their relative contribution to the size and persistence of earnings and wage losses for high-tenure workers. To this effect I build and estimate a quantitative, structural search model of the labour market with the following ingredients: heterogeneous firms, on-the-job search, specific and general human capital accumulation and endogenous job loss. The model is estimated by simulated method of moments using matched employer-employee data on Germany. It can reproduce the size and persistence of post-displacement earning and wage losses observed in the data. Counterfactual simulations reveal that the main mechanism that generates such post-displacement earning losses is the divergence in the evolution of specific (mostly) and general human capital paths of displaced workers relative to their non displaced colleagues.

More specifically, in this model both unemployed and employed workers sample job offers infrequently from an exogenous firm productivity distribution. Unemployed workers have a lower reservation productivity than employed workers, but once they become employed they climb the job ladder by accepting subsequent offers from more productive employers. Employed workers accumulate general human capital, which follows them through the course of their career when moving to other employers or to unemployment, and specific skills that, in contrast, are only valuable within the current match. The model features endogenous match destruction. Therefore, as they climb the job ladder, workers sort into more productive jobs that are also more stable, meaning that they are less likely to be destroyed following adverse productivity shocks.

In this framework, high-tenure workers that experience a displacement event lose a relatively more productive and stable job and, in addition, specific skills acquired on the job. Furthermore, during unemployment, they are subject to depreciation of their generic skills, thereby exacerbating their losses. Upon re-employment, they are more likely to accept a low productivity job which, by also being less stable, does not favour the skill acquisition process, hindering the recovery in earnings and wages.

This model further predicts that, controlling for firms' heterogeneity, (i) wages increase with workers' experience and tenure, due to general and specific skill growth, (ii) job switching rates fall with job tenure, due to the accumulation of specific skills. This is a key innovation compared to the standard workhorse search model, which implies that the only source of wage growth is workers receiving alternative employment offers, and that the job switching rate is decreasing in job tenure unconditionally and only due to the selection effect implied by the job ladder.

Therefore, I use these moments calculated in the German matched employer-employee data - in addition to standard others - as primitives to retrieve information about the parameters governing the accumulation process of general and specific human capital. The model is able to replicate the (targeted) within firm returns to tenure and experience and the fall in the job switching rate with tenure within firm observed in the data. Additionally, it delivers large and persistent earning and wage losses that mimic the (not targeted) data counterpart. Specifically, it generates an initial drop in earnings equal to 35% relative to the counterfactual in the year of displacement, and subsequent losses of around 10% that persist for 10 years after the event. Just like in the data, most of the persistence in earning losses is due to wages, which drop by 10% and stagnate even upon re-employment. Additionally, the counterfactual analysis reveals that 47% of the present discounted value of the wage losses is due to the loss of specific human capital, 34% to general human capital and the remaining 19% to the loss of a good job.

The key contribution of this work is that it provides a measurement framework to analyse the relative contribution of the possible drivers of the post-displacement earning losses. It does so by considering specific and general human capital accumulation in a model of job search with endogenous separation, and by pinning down the relevant parameters using both moments on separation and within firm wage growth, computed in a sample that is consistent with the one used for the estimation of the earning losses.

This paper is related to a number of contributions: one that focuses on post-displacement earning losses (Jarosch, 2015; Krolikowski, 2017; Jung and Kuhn, 2018; Huckfeldt, 2018; Burdett, Carrillo-Tudela, and Coles, 2020) and one that looks at the determinants of labour market earnings dynamics (see Topel, 1990; Dustmann and Meghir, 2005; Yamaguchi, 2010; Postel-Vinay and Turon, 2010; Altonji, Jr., and Vidangos, 2013; Bagger et al., 2014, among others).

The idea of modelling a job ladder in firms' productivity with endogenous separation is also present in Krolikowski (2017) and Jung and Kuhn (2018). Both papers are able to explain large and persistent earning losses for the Unites States by matching mostly moments related to workers' mobility, and deliver very close estimates of wage losses for the first five years from the event. In both papers the job ladder plays the biggest role in explaining post-displacement earning losses. Human capital does not feature in Krolikowski (2017) and in Jung and Kuhn

(2018) workers' skills count marginally. In the work of Jung and Kuhn (2018) wage dynamics are mainly driven by search and the job ladder, and the parameters that govern the process of human capital accumulation are estimated by matching moments on separation rates by age for workers with the same tenure, under the assumption that skills endogenously reduce workers' probability of separation by increasing match productivity. What sets apart this paper from Krolikowski (2017) and Jung and Kuhn (2018) is that I consider specific and general human capital as main drivers of wage growth alongside search, and use within firm returns to tenure and experience to directly learn about their evolution overs workers' career. This results in specific and general human capital playing the most important role in the explanation of wage losses.

The importance of workers' skills for understanding the long term consequences of job loss is also highlighted in other papers. For example, Huckfeldt (2018) stresses the role of occupation-specific skills and skill obsolescence during unemployment, Jarosch (2015) shows that the loss in job stability paired with skill loss during unemployment is responsible for most of the sluggish post-displacement wage recovery, and Burdett, Carrillo-Tudela, and Coles (2020) highlight the importance of forgone skill accumulation after displacement events.

The current work shares several similarities with Jarosch (2015). Both papers feature a job ladder with heterogeneous separation rates into unemployment and stochastic general human capital accumulation (decumulation) during employment (unemployment). One main difference between the two papers is that Jarosch (2015) models exogenous heterogeneous separation rates along the job ladder which are negatively correlated with match productivity, while this paper delivers mutually efficient match destruction events for low productive matches endogenously. Furthermore, this paper considers specific human capital accumulation as an additional channel to explain both wage dynamics and post-displacement wage losses for high-tenure workers, and links the process of human capital accumulation directly to returns to tenure and experience observed in the data.

Similarly, Burdett, Carrillo-Tudela, and Coles (2020) estimate a model of on-the-job search, accumulation of general human capital during employment and skill loss during unemployment to identify the causes of the cost of job loss. In contrast with the rest of the papers mentioned above, heterogeneity in separation rates along the job ladder is not taken into account.

In both the works of Jarosch (2015) and Burdett, Carrillo-Tudela, and Coles (2020), general human capital plays the biggest role in the post-displacement wage losses explanation. The underlying mechanisms, however, are different. In Jarosch (2015), high-tenure workers that fall off the ladder lose job security and experience repeated unemployment spells which, paired with a high estimate of depreciation rate of skills during unemployment, hinder wages and earnings recovery. In Burdett, Carrillo-Tudela, and Coles (2020), fast and constant accumulation rates of general human capital for workers that do not experience layoff, paired with long permanence into unemployment for displaced workers, prevents the convergence of wages after displacement.

These results show that the estimated parameters governing the general human capital accumulation process play a crucial role in the determination of the sources of the cost of job loss. The importance of skill decay in the wage losses decomposition in Jarosch (2015) is driven by the estimated general human capital decumulation rate during unemployment, equal to 23% per year, and accumulation rate during employment, equal to 2.4% per year. As remarked in Chapter 1, these estimates are obtained without explicitly matching moments related to wage-experience profile. This approach is likely to deliver distorted estimates of the parameters governing general human capital, given its fundamental role in explaining wage dynamics, which is not accounted in this work but heavily stressed in the literature (see for example Topel, 1990; Dustmann and Meghir, 2005; Lazear, 2009; Yamaguchi, 2010; Altonji, Jr., and Vidangos, 2013; Bagger et al., 2014, among others).

Burdett, Carrillo-Tudela, and Coles (2020), on the other hand, by targeting returns to experience, obtain a much lower skill decay rate during unemployment (equal to 1.7% per year) and higher skill accumulation rate during employment (equal to 4.5% per year). One shortcoming in their approach is that returns to experience are computed on the whole sample of male workers - rather than on the sample of workers compatible with the earning losses estimation (e.g. those with more than three years of experience) - and without taking into account firm and tenure effects. As stressed in Chapter 1, this delivers higher estimates of returns to experience compared to the literature (for example to Dustmann and Meghir, 2005) which, paired with their assumption of constant accumulation rates of general human capital, entails the risk overestimating the role of general human capital.

Starting from these considerations, the current paper uses within firm returns to experience and tenure, estimated on a sample which is consistent with the estimation of post-displacement earning losses, as key information on the evolution of general and specific human capital. In this way, this work provides a general framework to understand wage dynamics, heterogeneous job stability along the job ladder and to have a better understanding of the relative contribution of the different drivers of post-displacement earning losses.

The rest of the paper is organised as follows. Section 2.2 describes the model in detail. Section 2.3 describes the data, the identification strategy and the estimation results. In Section 2.4 I focus on the analysis of the long term consequences of job loss and on the counterfactual analysis. Finally, Section 2.5 concludes.

2.2 The Model

The theoretical framework is based on the seminal work by Postel-Vinay and Robin (2002). It is a partial equilibrium model of the labour market with on-the-job search and bargaining, and is enriched with workers' human capital accumulation and endogenous separation.

2.2.1 Ingredients

Agents Time is discrete and infinite and the economy is populated by risk neutral workers and firms. Firms are heterogeneous in productivity θ. Realizations of firms' productivity are drawn from an exogenous distribution $F(\theta)$ and constant throughout time.

In every period a fraction κ of the labour force is replaced by an equal mass of unemployed new entrants. New entrants are all identical. While employed, workers can accumulate both general and specific human capital. General human capital is accumulated at rate ϕ_e and is vested in the worker upon separation. However, it decays at rate ϕ_u during unemployment. Specific human capital is accumulated at rate γ during employment and, in contrast with general human capital, is completely lost upon transiting into unemployment or to other firms during employment.

Matching and Production The labour market is characterised by search frictions and there is on-the-job search. This implies that unemployed and employed workers can sample job offers from the exogenous distribution $F(\theta)$ at rates λ_0 and λ_1, respectively. The on-the-job search assumption induces a job ladder in productivity that workers climb over the course of their career.

When a worker and a firm meet and decide to form a match, they produce output equal to $y = f(\theta, s, g, \varepsilon)$, that depends on the fixed firm-productivity component θ, on the level of accumulated specific and general human capital, s and g, and on a time varying stochastic productivity component, ε. The initial realization of ε is equal to ε_0 in all new matches, and its subsequent realizations are drawn from a distribution $H(\varepsilon)$ in each period of a surviving match. As in Mortensen and Pissarides (1994), the presence of the time-varying component of a match productivity ε leads to endogenous destruction events. In particular, when the realization of the shock is low enough, worker and firm agree to dissolve the match. Additionally, the match faces a probability δ of being exogenously destroyed.

Timing of the events within one period All workers start every period inheriting state variables from the previous period. The timing of events for unemployed and employed workers is summarised in Figure 2.1 and 2.2.

Unemployed workers

At the beginning of the period, an existing unemployed worker with accumulated level of general human capital g dies with probability κ. If this happens, he/she is replaced in the next period by one newborn unemployed worker, endowed with the lowest level of general human capital, denoted by g_0. If the κ-shock is not realised, the worker stays in the labour market and faces the possibility of seeing the previously accumulated general human capital g depreciate with probability ϕ_u.

After the worker's general human capital level for the following period is realised, he/she can receive a job offer with exogenous probability λ_0, from a firm with productivity drawn from $F(\theta)$ distribution. If the match is profitable, the following period the worker is employed in firm θ and produces output $y(\theta, s, g, \varepsilon)$ is realised and the worker receives a fixed wage w, set following the bargaining protocol, explained in Section 2.2.2.

Employed workers

A worker employed with specific human capital s and general human capital g in a match with a firm of productivity type θ and time-varying productivity component ε, can exit the labour market in the following period with probability κ and be replaced by a new born unemployed worker with lowest level of general human capital, denoted by g_0. If the κ-shock does not realise, the employed worker stays in the labour market, and can see the level of general human capital increase with probability ϕ_e. After this, an exogenous separation shock can occur with probability δ, causing the destruction of the match and the transition of the worker into unemployment in the following period. If, however, the match continues, the following events can realise.

First, the worker accumulates specific human capital with probability γ. Second, the time-varying component of the match productivity ε is realised. And, finally, with probability λ_1 the worker can receive outside offers from the firm distribution $F(\theta)$. In this case, the worker can move to the poaching firm or stay with the incumbent. If he/she stays with the incumbent employer, the wage may be renegotiated following the rules explained in Section 2.2.2. Notice that in the decision of quitting to a new firm or to stay and renegotiate the wage, the new values of s, g and ε are taken into account, together with the value of the productivity of the current firm, and the poaching firm. If no offers are received, the worker and firm decide whether to continue the match or destroy it, given the new observed values of s, g and ε.

2.2.2 Workers Mobility and Bargaining Protocol

As we have seen in the previous section, at the end of the time period, after all the shocks are realised, unemployed and employed workers face several decisions. Unemployed workers have to decide whether to stay in unemployment or to accept a job offer at hand. Employed workers decide whether to continue the match at the offered wage under complete information.

The wage setting mechasism used in this model is based on the model of efficient rigid wages first pioneered in MacLeod and Malcomson (1993) and formalized in the context of a structural job search model in Postel-Vinay and Turon (2010).[1]

Unemployed workers that receive a job offer above their reservation productivity negotiate their wage according to the standard Nash-bargaining surplus sharing rule. As for employed workers, their wage is given by the current contract wage unless it is renegotiated by mutual consent, which means that one of the party has a credible threat to leave the match. Specifically, the contract can be renegotiated for two reasons: contact from another firm, which leads to a *trilateral* renegotiation between the worker, the incumbent and the poaching firms, and a significant change in the time-varying component of match productivity, which leads to a *bilateral* renegotiation between the worker and the firm.

Below, I explain in detail the workers' mobility decision and wage determination process for unemployed and employed workers in both cases of trilateral and bilateral renegotiation.

Unemployed workers An unemployed worker with level of general human capital g enjoys unemployment continuation value $U(g)$. When he/she samples a job offer from a firm with productivity θ, both parties observe the total value of the match. This is defined as the sum of the value of the match to the worker, net of the value of unemployment, and the value of the match to the firm. Specifically

[1] In a parallel work, Yamaguchi (2010) uses the same wage setting rule to explain wage dynamics.

the total surplus of the match is given by:

$$S(\theta, s_0, g, \varepsilon_0) = \big(W(\theta, s_0, g, \varepsilon_0, w_0) - U(g)\big) + J(\theta, s_0, g, \varepsilon_0, w_0) \tag{2.1}$$

where $\big(W(\theta, s_0, g, \varepsilon_0, w_0) - U(g)\big)$ and $J(\theta, s_0, g, \varepsilon_0, w_0)$ represent the net value of the match to the worker and to the firm, respectively. Notice that, since this is an initial match, the values of ε and s are fixed to ε_0 and s_0.

The possible outcomes for this scenario are:

1. $S(\theta, s_0, g, \varepsilon_0) < 0$: the match is unproductive. In this case the worker stays in unemployment and enjoys (net) continuation value equal to 0.

2. $S(\theta, s_0, g, \varepsilon_0) \geq 0$: the match is productive. In this case the worker and firm form the match, production takes place and the worker is paid a salary w_0 determined by the Nash bargaining surplus splitting rule, which assigns continuation value to the worker (firm) equal to a share α $((1-\alpha))$ of the total value of the match. Specifically, the initial wage w_0 is set following equation (2.2):

$$w_0 : W(\theta, s_0, g, \varepsilon_0, w_0) - U(g) = \alpha S(\theta, s_0, g, \varepsilon_0) \tag{2.2}$$

Employed workers and trilateral bargaining When a worker with level of general human capital g and specific human capital s, employed in a firm with fixed productivity θ and time-varying productivity ε, is contacted by a firm with productivity θ', there can be two situations that can arise:[2]

1. $S(\theta', s_0, g, \varepsilon_0) > S(\theta, s, g, \varepsilon)$: the surplus of the match with the poaching firm is higher than the current surplus. In this case, the worker will move to the poaching firm and the initial wage is set such that the worker extracts the whole surplus from the incumbent (least productive) firm and a share of the net surplus of the poaching (most productive) firm, proportional to his or her bargaining power, α. Specifically, w_0 is such that condition (2.3) is satisfied:

$$w_0 : W(\theta', s_0, g, \varepsilon_0, w_0) - U(g) = S(\theta, s, g, \varepsilon) + \alpha(S(\theta', s_0, g, \varepsilon_0) - S(\theta, s, g, \varepsilon)) \tag{2.3}$$

[2]For brevity of exposition I am assuming that the values of the surplus for both poaching and incumbent firms are positive, and that the value of the match to the firm and to the worker are always positive. However, these conditions can be violated and the rules of bilateral bargaining should be applied. This will be clearer in the exposition of the value functions.

The implied (net) payoffs for the worker and the firm are, respectively, $\{S(\theta, s, g, \varepsilon)) + \alpha(S(\theta', s_0, g, \varepsilon_0) - S(\theta, s, g, \varepsilon)); (1 - \alpha)(S(\theta', s_0, g, \varepsilon_0) - S(\theta, s, g, \varepsilon))\}$.

2. $S(\theta', s_0, g, \varepsilon_0) \leq S(\theta, s, g, \varepsilon)$: the surplus that is generated from the match with the poaching firm is lower than or equal to the surplus generated from the match with the incumbent. In this case, the worker will decide to stay in the current match. The possible outcomes that arise from this situation are the following:

   (a) $W(\theta, s, g, \varepsilon, w) - U(g) < S(\theta', s_0, g, \varepsilon_0)$: the workers' net value of the match with the incumbent firm is lower than the total value of the match with the poaching firm. In this case the worker has a credible threat to leave the match and the wage contract is revised upward, such that the worker extracts the whole surplus from the poaching (least productive) firm and a share α of the net surplus of the incumbent (most productive) firm. Specifically, the new wage w' satisfies equation (2.4):

   $$w' : W(\theta, s, g, \varepsilon, w') - U(g) = S(\theta', s_0, g, \varepsilon_0) + \alpha\big(S(\theta, s, g, \varepsilon) - S(\theta', s_0, g, \varepsilon_0)\big) \tag{2.4}$$

   The worker and the firm, respectively, enjoy a (net) payoff equal to $\{S(\theta', s_0, g, \varepsilon_0) + \alpha(S(\theta, s, g, \varepsilon) - S(\theta', s_0, g, \varepsilon_0)); (1 - \alpha)(S(\theta, s, g, \varepsilon) - S(\theta', s_0, g, \varepsilon_0))\}$.

   (b) $W(\theta, s, g, \varepsilon, w) - U(g) \geq S(\theta', s_0, g, \varepsilon_0)$: the worker's value of the match with the current firm is higher than the surplus generated with the poaching firm. In this situation the wage remains unchanged.

Employed workers and bilateral bargaining. The worker and the firm can also decide to terminate the match or renegotiate the wage without being contacted by a third party. This can happen following a significant change in the payoffs of worker and firm, due a innovation in the time-varying component of the match productivity. Specifically, the scenarios that may arise from this situation are the following:

1. $S(\theta, s, g, \varepsilon) < 0$: if the match becomes unproductive, the worker and the firm decide to destroy it. Their (net) payoffs of worker and firm in this situation are equal to 0.

2. $W(\theta, s, g, \varepsilon, w) - U(g) < 0$, and $S(\theta, s, g, \varepsilon) > 0$: if the workers' net value of the match is negative, but the match is still productive, then the worker

has a credible threat to leave and the wage is revised up to w', such that condition (2.5) is satisfied:

$$w' : W(\theta, s, g, \varepsilon, w') - U(g) = 0 \tag{2.5}$$

This means that the worker is indifferent between staying and going into unemployment. In this situation, the (net) payoffs enjoyed by the worker and the firm are, respectively, $\{0; S(\theta, s, g, \varepsilon)\}$.

3. $J(\theta, s, g, \varepsilon, w) < 0$, and $S(\theta, s, g, \varepsilon) > 0$: if the value of the match to the firm is negative and the surplus is still positive, the firm has a credible threat to leave the match and so the wage is revised downward up to w', so that condition (2.6) is satisfied:

$$w' : W(\theta, s, g, \varepsilon, w') - U(g) = S(\theta, s, g, \varepsilon) \tag{2.6}$$

This means that the firm is indifferent between staying and destroying the match, In this situation, the (net) payoffs enjoyed by the worker and the firm are, respectively, $\{S(\theta, s, g, \varepsilon); 0\}$.

2.2.3 Value Functions

Having presented all the key elements of the model, I can now present the formal recursive equations.

The present value of unemployment for a worker with general human capital g, is denoted by $U(g)$, and is determined by the following asset pricing equation:

$$U(g) = z(g) + \beta(1-\kappa)\mathbb{E}_{g'|g,u}\left\{U(g') + \lambda_0 \int Max(0, \alpha S(x, s_0, g', \varepsilon_0))dF(x)\right\} \tag{2.7}$$

where β denotes the discount factor. Equation (2.7) states that an unemployed worker enjoys today a flow of income proportional to the accumulated level of general human capital, $z(g)$, and tomorrow, conditional on remaining in the labour market, which happens with probability $(1-\kappa)$, the discounted expected value of remaining in unemployment (second term in the equation) plus the expected value of being in contact with a firm (third term in the equation).[3] Notice that the expected value of remaining in unemployment depends on the evolution of

[3]The stream of income received during unemployment, $z(g)$, can be interpreted as unemployment benefit or home productivity.

general human capital.

The present value of employment satisfies the following asset pricing equation:

$$
\begin{aligned}
&W(\theta,s,g,\varepsilon,w) = w + \beta(1-\kappa)\delta\mathbb{E}_{g'|g,e}U(g') + \beta(1-\kappa)(1-\delta)\Bigg\{\\
&(1-\lambda_1)\mathbb{E}_{s'|s}\mathbb{E}_{g'|g,e}\int Max\big(U(g'); Min(U(g')+S(\theta,s',g',\varepsilon'); W(\theta,s',g',\varepsilon',w)\big)\\
&dH(\varepsilon'|\varepsilon) + \lambda_1\mathbb{E}_{s'|s}\mathbb{E}_{g'|g,e}\int\int \mathbb{1}\big(S(x,s_0,g',\varepsilon_0) > S(\theta,s',g',\varepsilon')\big)\\
&Max\big(U(g'); U(g') + \alpha S(x,s_0,g',\varepsilon_0) + (1-\alpha)Max(0,S(\theta,s',g',\varepsilon')\big) +\\
&\mathbb{1}\big(S(x,s_0,g',\varepsilon_0) \leq S(\theta,s',g',\varepsilon')\big)\\
&Max\big(U(g'); Min(U(g')+S(\theta,s',g',\varepsilon'), W(\theta,s',g',\varepsilon',w));\\
&U(g') + S(x,s_0,g',\varepsilon_0) + \alpha(S(\theta,s',g',\varepsilon') - S(x,s_0,g',\varepsilon_0))\big)dH(\varepsilon'|\varepsilon)dF(x)\Bigg\}
\end{aligned}
\tag{2.8}
$$

Equation (2.8) states that in the current period an employed worker enjoys a wage equal to w. In the following period, conditionally on staying in the labour market, which occurs with probability $(1-\kappa)$, the worker faces different scenarios. All the payoffs associated to these scenarios are discounted by β.

First, the worker can be hit by an exogenous δ-shock and transition into unemployment (second term in the equation). Notice that the timing of the events imply that the general human capital shock hits first, so the worker's continuation value of unemployment is $\mathbb{E}_{g'|g,e}U(g')$.

Second, following an innovation in the time-varying component ε of the match productivity, the worker and the firm decide whether to destroy or continue the match, taking into account the new levels of specific and general human capital. If the match continues, worker and firm can decide whether to renegotiate the wage, following the rules described in the bargaining protocol section (third term of the equation).

Third, the worker can be contacted by a poaching firm with probability λ_1. If the match with the poaching firm is more productive than the current one, the worker leaves the incumbent employer. The indicator function $\mathbb{1}\big(S(x,s_0,g',\varepsilon_0) > S(\theta,s',g',\varepsilon')\big)$ captures this outcome. Notice that timing implies that the new values of s', g' and ε' are taken into account in the choice of staying or joining the poaching firm.[4] If, on the other hand, the match with the poaching firm is less productive than the current one, as indicated by the term $\mathbb{1}\big(S(x,s_0,g',\varepsilon_0) \leq$

[4]Notice that, since the timing assumption implies that the shock ε occurs and is observed before the offer, the value of the current match is the $Max\big(0; S(\theta,s',g',\varepsilon')\big)$.

$S(\theta, s', g', \varepsilon')\big)$, multiple scenarios open:

1. $S(\theta, s', g', \varepsilon') < 0$, the current match may become unproductive after a bad realization of ε and the worker transitions into unemployment.

2. $S(\theta, s', g', \varepsilon') \geq 0$, $W(\theta, s', g', \varepsilon', w) \leq U(g') + S(\theta, s', g', \varepsilon')$ and $U(g') + S(x, s_0, g', \varepsilon_0) > Max(U(g'); W(\theta, s', g', \varepsilon', w))$. The match is productive and the worker has a credible threat to leave the match to join another firm. The wage is renegotiated upward, as described by equation (2.4).

3. $S(\theta, s', g', \varepsilon') \geq 0$, $W(\theta, s', g', \varepsilon', w) \leq U(g') + S(\theta, s', g', \varepsilon')$ and $U(g') > Max(U(g') + S(x, s_0, g', \varepsilon_0); W(\theta, s', g', \varepsilon', w))$. The match is productive and the worker has a credible threat to leave the match to transition into unemployment. The wage is bid up following equation (2.5).

4. $S(\theta, s', g', \varepsilon') \geq 0$, and $W(\theta, s', g', \varepsilon', w) > U(g') + S(\theta, s', g', \varepsilon')$.[5] The match is still productive, but the firm has a credible threat to leave the match. The wage is revised downward as shown in equation (2.6).

5. In all other cases, the worker enjoys continuation value $W(\theta, s', g', \varepsilon', w)$ and the wage is unchanged.

The present value of the match to the firm is determined by the following asset pricing equation:

$$
\begin{aligned}
&J(\theta, s, g, \varepsilon, w) = y(\theta, s, g, \varepsilon) - w + \\
&(1-\kappa)\beta(1-\delta)\Big\{(1-\lambda_1)\mathbb{E}_{s'|s}\mathbb{E}_{g'|g,e}\int Max\big(0; J(\theta, s', g', \varepsilon', w)\big)dH(\varepsilon'|\varepsilon) + \\
&\lambda_1\mathbb{E}_{s'|s}\mathbb{E}_{g'|g,e}\int\int \mathbb{1}\big(S(x, s_0, g', \varepsilon_0) \leq S(\theta, s', g', \varepsilon')\big) \\
&Max\big(0; Min\big(J(\theta, s, g, \varepsilon, w); (1-\alpha)(S(\theta, s', g', \varepsilon') - S(x, s_0, g', \varepsilon_0))\big)\big) \\
&dH(\varepsilon'|\varepsilon)dF(x)\Big\}
\end{aligned}
\tag{2.9}
$$

The first term on the right hand side of equation (2.9) is the value of the output produced in the match net of the wage paid to the worker. The second term is describes the payoff of the firm in case of no contact from a poaching firm. In this case, if the match is productive and the firm has a credible threat to leave, it can force a downward renegotiation of the wage to the point in which it is indifferent from staying and leaving. The continuation value of the firm in case of negative

[5] Notice that this condition is equivalent to $J(\theta, s', g', \varepsilon', w) < 0$.

match productivity is 0. The third term reports the payoffs of the firm in case the worker is contacted by a poaching firm. If the worker leaves the match, the firm's continuation value is 0. If the worker stays and the offer is relevant, there is wage renegotiation, where the firm gets a share $(1-\alpha)$ of the net match surplus.

Combining equation (2.7), (2.8) and (2.9), I arrive to the following expression for the present value of the match surplus.

$$
\begin{aligned}
&S(\theta, s, g, \varepsilon) = y(\theta, s, g, \varepsilon) - \\
&\left[z(g) + \beta(1-\kappa)\left[\mathbb{E}_{g'|g,u}U(g') + \mathbb{E}_{g'|g,u}\lambda_0 \int Max(0, \alpha S(x, s_0, g', \varepsilon_0))dF(x)\right]\right] + \\
&\beta(1-\kappa)\mathbb{E}_{g'|g,e}U(g') + \beta(1-\kappa)(1-\delta)\mathbb{E}_{s'|s}\mathbb{E}_{g'|g,e}\Bigg\{(1-\lambda_1) \\
&\int Max(0; S(\theta, s', g', \varepsilon')dH(\varepsilon)) + \lambda_1 \int\int Max(0; S(\theta, s', g', \varepsilon'); S(\theta, s, g, \varepsilon') + \\
&\alpha(S(x, s_0, g', \varepsilon_0) - S(\theta, s, g, \varepsilon'))dH(\varepsilon)dF(x)\Bigg\}
\end{aligned}
\tag{2.10}
$$

The first term on the right hand side of equation (2.10) represents the value of match productivity. The second term in square brackets is the option value of an employed worker, that is the forgone home productivity and the search technology accessible during non employment. The third term is the value of unemployment. The fourth term represents the value of the surplus in case of no outside offer, in which the match can either continue or be destroyed following a bad realization of the ε component of the match productivity. The fifth term represents the value of the surplus in event of outside offer, in which the worker can either move to the poaching firm or stay with the current one. Notice that the value of the joint surplus does not depend on the wage, since it only affects its redistribution and not its size.

The Surplus equation (2.10) can be solved as a contraction mapping, given the value of $U(g)$. Similarly, the unemployment value equation (2.7) can be solved as a contraction mapping given the value of the Surplus. Thus, $U(g)$ and $S(\theta, s, g, \varepsilon)$ are solved numerically and jointly, on a discretized space for the state variables $(\theta, s, g, \varepsilon)$. The equilibrium wage is uniquely determined so that the continuation value of the worker equals the payoffs obtained through bargaining following the rules described in Section 2.2.2. However, the derivation of an explicit solution for the equilibrium wage seems to be intractable, therefore, I follow and derive it numerically as explained in Appendix 2.A.1.

2.2.4 Model Mechanisms

This model can reproduce the large and persistent post-displacement earning losses suffered from high-tenured workers for several reasons.

First of all, the model features a job ladder in firm productivity. This is generated by the on-the-job search assumption. Each period, both unemployed and employed workers receive job offers. Unemployed workers accept job offers above their reservation productivity, while employed workers accept to move to the poaching firm only if this entails a career improvement. This implies that newly hired (from unemployment) workers are more likely to be employed by lower productivity firms, which pay lower wages, while continuously employed workers, having accumulated search capital during the course of their career, are more likely to be matched with higher productivity firms, which pay higher wages and are subject to less workers turnover. Therefore, through the lens of this model, a high-tenure worker that experiences displacement will be more likely to lose a good and well paid job at the top of the ladder, and by transitioning into unemployment, will have to re-start the search activity from the bottom. This gives rise to large earning losses following a single displacement event, whose persistence depends on the frequency of job offers.

Second, the wage setting mechanism of renegotiation by mutual consent described above represents an additional channel of persistence of the post-displacement earning losses for high-tenured workers. The fact that worker, incumbent and poaching employers engage in a trilateral bargaining game, in which the worker can use the less productive firm as outside option to renegotiate the wage implies that, by climbing the job ladder, workers not only gain better positions but also build up renegotiation rents. This particular bargaining protocol, pioneered in Postel-Vinay and Robin (2002) and extended in Cahuc, Postel-Vinay, and Robin (2006), implies that high-tenure workers lose negotiations rents more than just a good job after a layoff event. Notice that this wage setting mechanism also implies the presence of returns to experience and tenure, not only because of the selection mechanism generated by the job ladder, but also because of the accumulation of specific and general human capital, which increase the value of the surplus and therefore of the negotiation benchmark, which rises wage growth following a renegotiation.

Third, the model features endogenous separations. A bad realization of the time varying component of the match productivity, ε, can make the match no longer productive and induce worker and employer to destroy it and, respectively, to transition into unemployment and shut down. In a canonical job ladder model, jobs originating from unemployment are more likely to be characterised by a low value of the fixed component of match productivity θ, and therefore to become unproductive after a bad realization of ε. This gives rise to multiple correlated unemployment spells, and contributes to making earning losses more persistent.

Finally, the presence of specific and general human capital further hinders the recovery of earnings and wages after a job loss event for high-tenure workers. The higher stability of high-θ matches, which means lower job-to-job and job-to-unemployment transitions, favours the worker's accumulation of both specific and general human capital. Specific human capital can in fact only be accumulated and kept if the worker stays within the firm, while it is completely lost upon job-to-job and job-to-unemployment transition. General human capital is accumulated only during employment, while it is subject to depreciation during unemployment. Hence, workers in high-θ matches, are more likely accumulate specific and general human capital, that makes the match even more stable, further favouring the accumulation of skills.

Altogether, these features allow the model to generate large and persistent post-displacement earning losses, whose relative importance is explored in the quantitative analysis in the next section.

2.3 Quantitative Analysis

In this section I discuss the details of the quantitative analysis of this work. First, I describe the data used to estimate the model, then the empirical strategy and, finally, I present the results of the model estimation.

2.3.1 Data Description and Sample Selection

This study is based on the *Sample of Integrated Labour Market Biographies* (SIAB) provided by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB). The SIAB dataset covers a random sample of 2% of individuals that were employed subject to social security in Germany any time between 1974 and 2014, excluding only civil servant and self-employed workers.

The dataset contains detailed day-to-day information for 1,618,337 individuals on employment status (employed, unemployed), type of contract (full-time, part-time), occupation category and (daily) wages. Basic biographic information, like gender, age and education level of the workers, are also included. Additionally, the dataset reports the record of the workers' establishment identifier, along with some general information on the geographic location, sector of activity, median wage and basic employment structure characteristics (e.g number of full-time workers, part-time workers). The raw dataset comes in *spell* episodes of different length, with a maximum length of one year, because of the notification rules in the German statutory pension system.

For the empirical analysis, I drop all the spells that are shorter than a month and all the workers that are not observed for longer than a year. In case of multiple identical employment spells for the same worker, I keep the episode with the highest wage, and drop spells with daily wages below 10 Euros (in 2010 prices). Then, I convert the data from spell to monthly frequency, as described in Appendix 2.B.1.

Additionally, I apply the following sample selection criteria. I focus on male workers between 19 and 65 years old, employed only in West Germany. Since there is no information on working hours, I restrict the analysis only to full time workers. Employment histories are left censored, which means that workers can only be observed from 1975 onwards. I deal with this problem by keeping in the sample only workers that can be tracked from the beginning of their career, which is assumed to start only after completion of their studies. Specifically, I keep in the sample workers with no high school degree that are 19 years old when I first observe them. Workers that hold a high school degree have to be at most 22 years old; those that graduated from a technical college have to be at most 28 years old, and those that hold a university degree have to be at most 30, when they first enter the dataset.[6]

After applying these selection criteria, I end up with 153,996 workers in 247,903 firms, during the 1975-2014 time span.

2.3.2 Model Implementation

The model is solved numerically under the following assumptions.

I assume that output per period, Y_t, in a match between a firm with fixed productivity θ, and a worker that has accumulated specific and general human capital, s_t and g_t, that is hit by a productivity shock with realization ε_t, is given by:

$$Y_t = exp(\theta + s_t + g_t + \varepsilon_t) \tag{2.11}$$

I make the following parametric assumptions on the distributions governing firm level heterogeneity θ and the time-varying productivity component ε. The sampling distribution of firm level heterogeneity is Normal with mean 0, $\theta \sim$

[6] The variable schooling in the SIAB dataset has the problem of many missing values and inconsistent reporting. I deal with this issue using the imputation procedure suggested in Fitzenberger, Osikominu, and Völter (2005).

$N(0, \sigma_\theta)$. The idiosyncratic component of the match productivity ε is assumed to follow a AR(1) process:

$$\begin{aligned} \varepsilon_t &= \rho_\varepsilon \varepsilon_{t-1} + u_t, \\ u &\sim N(0, \sigma_\varepsilon) \end{aligned} \tag{2.12}$$

The value of ε_0 in every initial match, coming from employment and unemployment, is denoted as ε_0 and it is set to the median value of the unconditional distribution of ε. Both θ and ε are discretized using the Rouwenhorst (1995) method, respectively to 15 and 7 grid points.

The grid for general human capital, g, is made of 5 equidistant points within the values $[g_0, \overline{g}]$, where g_0 is normalised to 0. Both processes of accumulation during employment and de-cumulation during unemployment of general human capital are state-dependent, and have transition matrices $P_{g|e}$ and $P_{g|u}$ listed below:

$$P_{g|e} = \begin{bmatrix} 1-\phi_e & \phi_e & 0 & 0 & 0 \\ 0 & 1-\phi_e & \phi_e & 0 & 0 \\ 0 & 0 & 1-\phi_e & \phi_e & 0 \\ 0 & 0 & 0 & 1-\phi_e & \phi_e \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$P_{g|u} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \phi_u & 1-\phi_u & 0 & 0 & 0 \\ 0 & \phi_u & 1-\phi_u & 0 & 0 \\ 0 & 0 & \phi_u & 1-\phi_u & 0 \\ 0 & 0 & 0 & \phi_u & 1-\phi_u \end{bmatrix}$$

Similarly, the grid for specific human capital s is made of 5 equidistant points within the values $[s_0, \overline{s}]$, where s_0 is normalised to 0. The process of accumulation of specific capital throughout the duration of a match is state dependent and has transition matrix P_s. The matrix P_s looks like:

$$P_s = \begin{bmatrix} 1-\gamma & \gamma & 0 & 0 & 0 \\ 0 & 1-\gamma & \gamma & 0 & 0 \\ 0 & 0 & 1-\gamma & \gamma & 0 \\ 0 & 0 & 0 & 1-\gamma & \gamma \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Furthermore, I assume that the income received during unemployment is proportional to the level of general human capital accumulated by the worker, specifically:

$$Z(g_t) = exp(p_z + g_t) \tag{2.13}$$

Finally, I set the frequency of the time period to one month.

Given this set of assumption, I am left with 13 parameters to calibrate. These are summarised and listed in Table 2.1.

2.3.3 Calibration and Identification Stategy

In order to calibrate the parameters of the model I use a mix of moments from the data and estimates from reduced form regressions as empirical targets. For this reason the approach is closely related to indirect inference. In total, I target 16 over-identifying restrictions to calibrate 13 parameters. It is important to keep in mind that the model parameters are calibrated jointly. This means that, even if it can be argued that some moments are more informative to pin down certain parameters, all the parameters indirectly play a role in the determination of each moment.

Transition parameters and workers' bargaining power. The parameter κ, that governs the entry/exit from the labour market, is calibrated to match the observed average age in the dataset. Specifically, it is set equal to 0.006, to obtain a average age in the simulation of the model close to 31 years old, which is the one observed in the data.[7]

In order to inform about the parameters governing job transitions to another job and to unemployment, λ_1 and λ_0, I follow Jarosch (2015) and use the observed rate of job-to-job transition (E–E) and the average unemployment rate in Germany in the 1975-2015 years - this last one computed using national accounting data -, respectively. An increase in the contact rate during employment should in fact increase the probability of job switching, and a higher contact rate during non-employment should be associated to a lower unemployment rate.[8]

The observed average probability of separation into non-employment (E–N) among workers with more than three years of tenure informs us about the parameter δ that governs exogenous separation (a more detailed explanation is given in the next paragraph).

I follow Jarosch (2015) and use the ratio between average wages of people exiting non-employment and average wages ($w_0/\overline{w}$) to inform about α. As α gets bigger the disadvantage of newly hired workers diminishes, implying a higher $w_0/\overline{w}$ ratio.

[7] To be clearer, I set $\kappa = 0.006$ since $(1 \div \kappa) \times 12 = 13.8$. If we normalise the starting age to be 18 years old, the average age in the simulated dataset becomes 31.

[8] The unemployment rate in the model is computed using the flow balance equation for employment: $u = (EN + \kappa)/(EN + \kappa + NE)$.

Idiosyncratic component of match productivity distribution. In the model, more productive matches last longer and are more likely to survive negative idiosyncratic ε-shocks and to not get destroyed. This implies that the model generates declining probabilities of separation into non-employment by tenure. For this reason, I use the unconditional average separation rate into non-employment (E–N) for all workers and its (yearly) tenure profile to identify the parameters governing the distribution of the idiosyncratic component of match productivity $H(\varepsilon)$.[9] Specifically, I use the position of the E–N tenure profile to inform about the volatility of the ε-shocks, σ_ε, with higher volatility implying higher level of E–N average probability for any given level of tenure, while the slope helps identifying the persistence of the AR(1) process for ε, with higher steepness indicating higher persistence of the shock.

The fact that workers in high-tenure matches (with high productivity) face a non-zero probability of separation into non-employment in the data is explained by considering exogenous separation in the structural model.

Fixed component of match productivity distribution. The variance of wages helps identifying the parameters relative to the fixed component of the firm productivity, σ_θ.[10] The firm fixed component of match productivity plays in fact an important direct role in determining the wages, jointly with workers' human capital.

General and specific human capital. The parameters related to general and specific human capital are identified using both moments on wages and separation. Matched employer-employee data play a fundamental role in this case, allowing to separately identify the role of specific and general human capital from the job ladder in workers transition probability and wages.

As in standard on-the-job search models with matching of counter offers à la Postel-Vinay and Robin (2002) and Cahuc, Postel-Vinay, and Robin (2006), the model predicts wage growth with experience and tenure. Specifically, wages grow with experience because of the on-the-job search assumption, which allows workers to move towards better and higher paying matches throughout their career. Additionally, wages grow within the match due to the assumption of matching of counter offers, which allows workers to renegotiate their salary with the employer following relevant alternative job offers. In this theoretical framework, the presence

[9]Krolikowski (2017) uses the same identification strategy to inform about the parameters relative to the idiosyncratic component of the match productivity distribution.

[10]Specifically, I use wage residuals from a regression of log wages on tenure, experience controlling for year and individual fixed effects.

of general and specific human capital provides additional channels, alongside the job ladder, to explain the returns to experience and tenure. The longer the worker is employed, and also the longer the worker is employed within the same firm, the more likely it is that he/she acquires generic and specific skills that increase the match productivity. Being in a match with higher productivity implies a higher negotiation benchmark, and consequently a higher wage growth in case of relevant counter offers.

In light of this, within-firm reduced form estimates of returns to experience and tenure enable to retrieve information on the accumulation of human capital, net of the role of the job ladder. Specifically, I estimate the reduced form model presented in equation (2.14):

$$\begin{aligned} \ln w_{ijt} =& \alpha_i + \gamma_1 Exp_{t\in[1,12]} + \gamma_2 Exp_{t\in[12,24]} + \gamma_3 Exp_{t\in[25,36]} + \\ & \beta_1 Tenure_{ijt} + \beta_2 Tenure^2_{ijt} + \chi_1 Exp_{i,t-36} + \chi_2 Exp^2_{i,t-36} + \psi_j + y_t + \epsilon_{ijt} \end{aligned} \tag{2.14}$$

where the log-wage of individual i in firm j at time t is regressed on an individual fixed effect α_i, a series of dummies for experience in the first three years (expressed in months), a quadratic polynomial in tenure and experience for experience greater than three years (expressed in months), a firm fixed effect ψ_j computed as in Lamadon, Manresa, and Bonhomme (2016) and a time fixed effect y_t. The term ϵ_{ijt} represents the error term. I then use the estimated parameters $\hat{\beta_1}$, $\hat{\beta_2}$, $\hat{\chi_1}$, $\hat{\chi_2}$, as moments to target.

To convey information about the speed of accumulation of specific human capital, γ, I estimate equation (2.15) by OLS:

$$EE_{ijt} = \alpha_i + \beta_3 Tenure_{ijt} + \chi_3 Exp_{it} + \psi_j + y_t + \epsilon_{ijt} \tag{2.15}$$

where EE_{ijt} represents the average monthly job-to-job transition probability of individual i employed in firm j at time t; α_i is an individual fixed effect; ψ_j represents a firm fixed effect computed as in Lamadon, Manresa, and Bonhomme (2016); y_t is a year fixed effect and, finally ϵ_{ijt} represents the error term. In the spirit of indirect inference, I use the estimated $\hat{\beta_3}$ as a target and run the same regression on model-generated data. In this model, workers can in fact increase their productivity as they stay longer within the firm by accumulating specific human capital, which - in opposition to general human capital that is fully transferable - is completely lost when transitioning into another firm or non-employment. This implies that the incentive of switching jobs declines with workers' tenure within the firm, even once we take into account firm's tome-invariant component of match productivity (using firms' fixed effects). The steeper (flatter) is the E–E - tenure relation, the fastest (slowest) will be the accumulation rate of specific human capital.

I use firms fixed effects computed as in Lamadon, Manresa, and Bonhomme (2016) for two reasons. First, because of the issue of limited mobility bias, which makes the estimates with standard firms fixed effects inaccurate. Second, in the SIAB-7514 dataset I only observe 2% of the total population of German workers. Therefore using the standard firm fixed effects would inaccurately control for firms' time invariant characteristics. Specifically, I use k-means algorithm to classify firms in five groups, based on the information on average wages by firm provided by the establishment side of the dataset, and use the obtained groups identifiers as firm fixed effects. The procedure is explained in detail in Appendix 2.C.

Finally, to have information on the parameters that govern the rate of decay of general human capital during non-employment I estimate equation (2.16) by OLS:

$$\ln w_{it}^{0} = \alpha_i + \pi dur_{it}^{NE} + y_t + \epsilon_{it} \tag{2.16}$$

where the (log) of re-employment wages after non-employment spells (w_0) is regressed on the length of the non-employment spell (in months), controlling for individual and time fixed effects. The estimated coefficient $\hat{\pi}$ is used as a target.

Notice that this set of moments is computed only on the sub-sample of workers that have been in the labour market for more than three years. This is done to be consistent with the sample used in the estimation of the empirical job displacement earning and wage losses, which is based on job loss events for high-tenure workers only, that are those with more than three years of tenure and consequently with minimum three years of experience (see Section 2.4).

The model aims in fact at explaining the observed post-displacement earning and wage losses and at quantifying the relative importance of the channels of the job ladder with endogenous separation, general and specific human capital. We know from the literature that the first years in the labour market are generally characterised by more frequent job-to-job transitions and higher returns to experience. This is confirmed in the SIAB 7514 dataset. In fact, the average rate of job-to-job transition on the overall sample is equal to 0.103, while in the sub-sample of workers with more than three years of experience it is equal to 0.0087. As for returns to experience, Figure 2.3 reports the estimates obtained considering both workers' total experience and workers' experience truncated at year three of their career.[11] As we can see, returns to experience are much higher

[11] In practice, in order to avoid positive selection bias, I obtain the estimates for returns to

and more concave if we consider the total workers' career. As such, by targeting average job-to-job transition rates and returns to experience including the first three years of workers' career, I would face the risk of overestimating the role of the job ladder and/or general human capital, given that earning losses are computed on workers with more than three years of tenure (and experience).

Calibration Method The model parameters are calibrated using Simulated Method of Moments. Specifically, the parameters are chosen so that the distance between a vector of data-moments and a vector of model-generated moments is minimized. That is, the vector of model parameters, $\hat{b}$, is chosen so that equation (2.17) is satisfied:

$$\hat{b} = \underset{b}{\operatorname{argmax}} - (\hat{m} - \tilde{m}(b))' W (\hat{m} - \tilde{m}(b)) \tag{2.17}$$

where $\hat{m}$ represents the vector of data moments, $\tilde{m}$ represents the vector of model-generated moments, W is a weighting matrix and b indicates the vector of parameters.

The model-generated data are obtained by simulating the model to create an artificial dataset of employment histories and wages series, which resembles the true dataset.

The optimization is implemented using a global optimization algorithm that is suggested in Guvenen *Computational and Empirical Methods for Dynamic Economics*. The procedure is explained in detail in Appendix 2.A.2.

2.3.4 Model Fit

In Table 2.2 I report the values of the moments discussed in Section 2.3.3 estimated on the SIAB data, together with their model generated counterpart. The calibrated parameters are shown in Table 2.3.

The model fits the data reasonably well. It is able to replicate the estimates of employment-employment transition and unemployment rates. It also reproduces the declining employment to non-employment separation rates with tenure estimated in the SIAB-7514 dataset. Specifically, I find that workers with up to one year of tenure face a probability of exiting employment close to 3% per month in the first year, while workers with two years of tenure see this probability more than halved, and declining further if they stay longer with the firm. This is possible

experience truncated at year three of workers' career, by including dummies for the first three years of job experience, and fitting a second order polynomial in experience for the rest of the time spent on the labour market as explained in equation (2.14).

because I model endogenous separation, by taking into account the idiosyncratic component of the match productivity, that follows the distribution of $H(\varepsilon)$. It is worth mentioning that the calibrated parameters that govern $H(\varepsilon)$ (σ_ε and ρ_ε) are in line with Krolikowski (2017), who reports values of 0.53 and 0.79 respectively for standard deviation and persistence of $H(\varepsilon)$, versus 0.62 and 0.73 calibrated in this work.

The model slightly over-estimates the variance of wages, delivering a value of 0.069 versus the 0.042 estimated in the data, and also of min-mean wage ratio with a value of 0.881 versus 0.739 in the data. The calibrated value for the standard deviation of the fixed component of the firm productivity distribution, $F(\theta)$, is equal to 0.06. This is much lower than the estimate of Krolikowski (2017), due to the fact that in this work general and specific human capital are taken into account as sources of wage dispersion and wage growth in addition to firms' productivity.

The model also captures the negative relationship between E–E and tenure fairly well. When equation (2.15) is estimated on the model generated data, I find a negative coefficient $\hat{\beta}_3$, which implies that staying with the firm for one additional year reduces the average E–E rate by 0.03%, versus the 0.05% estimated in the data.[12] This prediction of the model, confirmed by the data, sets further apart this work from the rest of the literature on the cost of job loss. Krolikowski (2017), for example, would imply a coefficient $\hat{\beta}_3$ statistically non different from zero. This is because tenure only represents a proxy for the selection process induced by the job ladder, which in this regression is absorbed by firm fixed effects. Similar conclusions can be deduced from Jung and Kuhn (2018), who also consider tenure as a proxy for the selection mechanism implied by the job ladder, and labour market experience as a proxy for general human capital accumulation. Additionally, they assume that general human capital is not neutral for workers' separation decision, since it is partly lost upon workers' transition. Therefore their model implication for the estimation of equation (2.15) would be a $\hat{\beta}_3$ coefficient non statistically different from zero, since firm fixed effects now explicitly account for selection, and a negative coefficient for $\hat{\chi}_3$, since general human capital is non neutral with respect to separation. This, however, contrasts with the data evidence that shows a negative and statistically significant coefficient for $\hat{\beta}_3$, and $\hat{\chi}_3$ non statistically different from zero.

The model delivers an almost exact fit for the returns to experience and tenure (see Figure 2.4). The coefficients estimated in the SIAB-7514 dataset imply,

[12] Even though the parameter estimated in the data is small it is economically relevant. Given that the average E–E rate is equal to 0.0087, the estimated $\hat{\beta}_3$ implies that staying with the firm for one additional month reduces the average E–E rate to 0.0082.

respectively, a 2.2% and 0.51% increase in (log) wages for each additional year of experience and tenure. The model counterparts are respectively 1.8% and 0.49%. Finally, the structural model reproduces the negative relationship between entry wages and time spent in non-employment estimated in the data. Specifically, in the data one more year spent in non-employment is associated to a reduction in (log) wages equal to 2.3%, versus the 2.8% that is produced by the model. Targeting these moments delivers calibrated values of the model parameters that imply a yearly accumulation rate of general and specific human capital equal to 2.2% and 0.4%, respectively, and a depreciation rate of general human capital equal to 5.5% per year.

These estimates differ from the ones obtained in Jarosch (2015) and Burdett, Carrillo-Tudela, and Coles (2020). Jarosch (2015) estimates a (yearly) rate of general human capital accumulation of 2.4% and a decumulation rate equal to 23% (per year), while Burdett, Carrillo-Tudela, and Coles (2020) calibrate a (yearly) accumulation rate of general human capital equal to 4.5% and a depreciation rate equal to 1.7%.[13]

As discussed in Chapter 1, the different calibration values depend on the different empirical strategies adopted in each paper. Jarosch (2015), for example, obtains a higher depreciation rate and a lower accumulation rate of general human capital compared to what is found in this work, because returns to experience are not explicitly taken as a primitive to inform about the learning by doing process. The correlation between initial wages (at re-employment) and length of the previous unemployment spell is used to calibrate the depreciation rate, while the appreciation rate is obtained indirectly, by imposing an equilibrium condition that ensures that unemployed workers lose general human capital as often as employed workers accumulate it.[14] However, ignoring returns to experience in a model with general human capital may provide distorted estimates of the accumulation and decumulation processes. In fact, both rates of general human capital accumulation during employment and decumulation during unemployment play a role in the reduced form estimation of the returns to labour market (actual) experience. The

[13]More precisely, Jarosch (2015) estimates a value of monthly accumulation (decumulation) rate for general human capital equal to 0.014 (0.131), on a grid of 7 equidistant point with maximum value equal to 2 and minimum equal to 1. Burdett, Carrillo-Tudela, and Coles (2020) calibrate their model for three different groups of workers, classified according to their education level. They find an accumulation rate of general human capital equal to of 4.9% for low educated workers, 4.1 for medium educated workers and 4.8% for high educated workers. The decumulation rate is equal to 1.7% for workers with medium and high education, and 1.2% for those with low education.

[14]The equilibrium condition imposed by Jarosch, (2015) is the following: $(1-\psi_e)^{u/(1-u)} = (1-\psi_u)$. Where u represents the unemployment rate, ψ_u the rate of decay of human capital during unemployment and ψ_e the accumulation rate of general human capital during employment.

first plays a direct role: the longer is the workers' actual experience, the higher the accumulated skills, which translate into higher wages. The second plays an indirect role: labour market actual experience is correlated with labour market potential experience, which includes periods of unemployment. The loss of human capital during unemployment reduces workers' productivity and wages, negatively affecting the estimated returns to actual experience.

On the other hand, Burdett, Carrillo-Tudela, and Coles (2020) target directly returns to experience in addition to the relation between re-employment wages and length of unemployment spell, and obtain accumulation rate of general human capital which is more than twice faster than what is found in this work and a significantly slower decumulation rates of general human capital. This discrepancy can be explained by the fact that Burdett, Carrillo-Tudela, and Coles (2020) target higher returns to experience in the data (on average equal to 4% per year compared to the 2.2% estimated in this work). This is because they estimate returns to experience using a Mincer regression framework in which (log) wages are regressed on a second order polynomial in actual experience and year fixed effects, omitting controls for tenure and firm fixed effects, and including early career workers. Their strategy delivers returns that are higher even compared to other works in the literature. For example, Dustmann and Meghir (2005), using a control function approach and focusing only on workers in new jobs after a displaced event, find that skilled workers' wages grow by 6% in the first years of work and decline to 1.2% after five years of experience and unskilled workers' wages grow by 8.2% in the first years of work and become zero after three years of experience. This is particularly relevant since post-displacement earning losses are computed on high-tenure workers which, as Dustmann and Meghir (2005) show, exhibit even lower returns to experience (equal to 1.2% and 0 for skilled and unskilled workers, respectively).

From this discussion it follows that taking into account returns to experience and tenure within a framework that aims at explaining the sources of wage growth in the years that follow a job loss event is extremely important. The main contribution of this paper in this sense is twofold: *(i)* it uses estimates of returns to experience, obtained by controlling for firms' fixed effects and focusing only on wage growth from year three of workers' experience, which coincides with the sample of workers used in the estimation of the earning losses, and *(ii)* it draws conclusion of general and specific human capital accumulation based on these estimates.

2.4 The Cost of Job Loss

This section presents the estimated earnings and wage losses for displaced workers computed on the SIAB-7514 dataset. I then compared them to the losses generated by the model, which are not targeted in the calibration. Finally, I perform a counterfactual analysis to identify the forces driving the wage losses.

2.4.1 Reduced Form Analysis

To compute earning and wage losses of displaced workers on the SIAB-7514 data, I first aggregate the frequency of time observations in the dataset from monthly to yearly as explained in Appendix 2.B.3. Then, I apply some further selection criteria to the yearly panel following Jarosch (2015). Specifically, I define a separation year y and I only consider workers that are between 25 and 54 years old in y and that are continuously employed within the firm recorded in y for at least years $y-1$, $y-2$ and $y-3$. Finally, I split the sample in treatment and control groups. The treatment group is made of workers that experience a separation into non-employment from the long-term employer in year y, and that return employed in a different firm by year $y+3$. The control group is made of workers that did not experience a separation from the long-term employer in year y.

On this sample, I then use the same specification as Davis and Wachter (2011) and estimate equation (2.18) for each displacement year y between 1985 and 2005:

$$e_{it}^y = \alpha_i^y + \gamma_t^y + \beta^y X_{it} + \sum_{k=-4}^{10} \delta_k^y D_{it}^k + u_{it}^y \tag{2.18}$$

where y indicates the displacement year, t is the time variable, i the indicator for the individual. The outcome variable e_{it}^y represents the real annual earnings for individual i at time t, the fixed effect α_i^y absorbs workers' heterogeneity, while γ_t^y represents a year fixed effect.[15] The vector X_{it} is a quadratic polynomial in age for individual i at time t, and D_{it}^k are dummy variables indicating if the worker was displaced k years before or after y. More explicitly, for displacement year y:

$$D_{it}^k = \begin{cases} 1, & \text{if } t-y=k \text{ and } EN_{i,t=y}=1. \\ 0, & \text{if } t-y \neq k \text{ or } EN_{i,t=y}=0\ . \end{cases} \tag{2.19}$$

I follow Jarosch (2015) and define $k=0$ as the last year of positive earnings with

[15] The outcome variable e_{it}^y is replaced by wages w_{it}^y and employment h_{it}^y when estimating the post-displacement wage and employment losses.

the pre-displacement employer, and $k = 1$ as the first year with zero earnings from the pre-displacement employer.[16]

I estimate equation (2.18) for each displacement year $y \in [1985, 2005]$ and obtain coefficients $\hat{\delta}_k^y$, that inform about the evolution of earnings $k = (-4, ..., 10)$ years before and after separation in year y. I then follow Jarosch (2015) and divide the coefficients by the corresponding counterfactual earnings for the treatment group in the corresponding year.[17] Then, I take the series of estimated coefficients as percentage of their counterfactual earnings and average them across all years $y \in [1985, 2005]$ to obtain an estimate for the post-displacement earning losses.

I plot the results for earnings, employment and wage losses estimated on the SIAB-7514 data in Figure 2.5. The results are in line with the ones found in the literature for Germany (Jarosch, 2015, Burdett, Carrillo-Tudela, and Coles, 2020): earnings of displaced workers drop in the year after separation by 40% relative the counterfactual and recover fast in the first years after displacement, getting to 20% after two years and to 10% after five years, but remain very persistent even after 10 years from the separation event. The decomposition of earnings into wages and employment shows that most of the size of the losses in the initial period is given by the losses in employment, while most of the persistence is attributable to wages. Wages drop initially by 10% and never recover, remaining almost 7% below their counterfactual path even after 10 years from the separation event. Employment losses show a substantial drop in the year after separation, but recover much faster than earnings. In fact, two years after the separation event employment losses reach 15% and from year four they stabilise at 5%.

From this picture it emerges that, compared to the results for earnings, wages and employment losses in the United States (see for example Huckfeldt, 2018), the German data exhibit a slower recovery of employment losses. This motivates the choice of modelling a job ladder with higher separation rates at the lower rungs, that implies serially correlated job loss events.[18]

2.4.2 Model versus Data

In this section I compare earnings, wages and employment losses estimated in the data with the theoretical counterparts obtained using the model generated

[16]For example, when estimating earning losses for displacement year $y = 1985$, $D^0_{i,1985}$ is equal to 1 in year $t = 1985$ if worker i experiences displacement during this year, and equal to 0 in all other years.

[17]The counterfactual earnings are obtained as the predicted values of the regression results for the treatment group after imposing all $D^k_{it} = 0$.

[18]This is in line with the work of Jarosch (2015), with the difference that in this work separations are endogenous.

data. The theoretical losses are estimated by applying the same sample selection and estimation method used for the empirical ones, with the only difference that individual fixed effects are omitted since the model does not consider individual heterogeneity.[19]

The results of the comparison are shown in Figure 2.6. The model generates estimates of earning losses close to the data counterparts and is also able to replicate the decomposition into employment and wages components. In the model, as in the data, the high peak in earning losses in the year after separation from the long term employer is given by losses in employment, while the persistence is mostly due to wages.

2.4.3 Structural Decomposition of Wage Losses

As shown in the previous subsections, the persistence of the earning losses experienced by workers after the separation event is mostly given by the losses in wages. This feature of the data is also very well replicated by the model. According to the model, job search, general and specific human capital are the three forces that can jointly explain the divergent path of wages of workers that experience a separation. To quantify the relative contribution of each of these forces, I use the calibrated model to build counterfactual wage series for workers who experience a separation event.

I proceed according to the following steps.

Step 1. I select workers in the treatment group for each separation year y and artificially set the exogenous separation event to 0 to compute the counterfactual series of wages, specific and general human capital for years $t \in (y, y + 10)$.

Step 2. I assign the counterfactual paths of general human capital obtained from Step 1, to the workers in the treatment group and compute the series of average wages for ten years after the separation event. The percentage deviation of this series of wages from the the counterfactual series computed in Step 1 represents the post-displacement wage losses not attributable to the loss in general human capital.

Step 3. I assign the counterfactual paths of both general and specific human capital obtained in Step 1 to the workers in the treatment group and compute the series of average wages for years for ten years after the separation event,

[19] I have also performed the estimation of the theoretical losses including individual fixed effects, and it does not affect the results.

to obtain the post-displacement wage losses not attributable to loss in general and specific human capital.

Figure 2.7 reports the results of this decomposition exercise. It is worth noticing that the counterfactual exercise produces wage losses very similar to the ones obtained with the regression framework, further validating the reduced form estimation approach. The blue, green and red areas in the graph respectively show the contributions of general human capital, specific human capital and job ladder to the total wage losses. The decomposition implies that 33.59% of the present discounted value of the wage losses is due to the loss in general human capital, 47.19% is due to the loss in specific human capital and the remaining 19.22% due to the loss of a good job. Interestingly, the exercise shows that all the three channels play an important and balanced role in explaining the peak in wages at the time of displacement. However, it is mostly the divergence in the evolution of specific and general human capital paths between the treated and the counterfactual groups that determines the persistence in the wage losses.

In light of these results, the mechanism behind the observed post-displacement wage losses is the following. When a high-tenure worker experiences displacement for exogenous reasons, he/she immediately loses a good job and specific human capital with probability 1 and, by spending time in non employment (on average 6 months given the estimated parameters) faces general human capital depreciation with probability 5.5% per year. At re-employment, the worker is more likely to end up in a low productive firm with no specific human capital. This makes the new match less stable and increases the worker's probability of falling into non-employment again. Eventually, given the frequency of job-to-job transitions in the data, the displaced worker climbs the job ladder and reaches a stable position: this is reflected in the role of the job ladder that shrinks through time and reaches the level of zero at year 10. However, after ten years the displaced workers do not fully recuperate specific (mostly) and general human capital compared to their colleagues in the counterfactual group, and this induces persistent losses in wages.

2.5 Conclusions

The economic literature documents two main empirical stylized facts: *i*) substantial returns to tenure and experience; *ii*) large and persistent post-displacement earning losses for high-tenure workers.

From a theoretical perspective, both facts can be explained by workers' job search activity and accumulation of specific and general human capital. In light of these considerations, I build a theoretical framework that includes these three channels to provide some insights on the drivers of both workers' earnings dynamics and post-displacement earnings losses. I use matched employer-employee data to compute moments related to job mobility and wage dynamics to obtain direct information on the process of job search and accumulation of general and specific skills. I use this evidence to simulate complete workers' job histories, which allow to replicate wage dynamics, post-displacement earning losses and their breakdown into the wage and employment components. The results of the counterfactual experiments document that the wage recovery of German workers that experience job loss is hindered by, in order of importance, a significant loss in specific human capital (47%), general skill decay during unemployment (34%) and the loss of a good job (19%).

Through the lens of the theoretical model presented in this paper, by transitioning into unemployment, high-tenure displaced workers lose a good job and specific human capital. The time spent in unemployment deteriorates their general skills. Being unemployed, they are more likely to accept lower productivity jobs. Being these jobs less stable because less likely to survive negative productivity shocks, they see their probability of falling again into unemployment increasing. This prevents them to rebuild the lost skills, slowing down the earnings recovery.

The major contribution of this work is to provide a measurement framework that can quantitatively account for the relative contribution of the forces driving the cost of job loss. It does so by taking as primitive information both moments on workers' separation and within firm wage growth, computed using matched employer-employee data and on a sample that is consistent with the one used for the estimation of the earning losses.

Understanding the sources of post-displacement earnings losses is of fundamental importance for designing efficient labour market policies aimed at reducing the impact of job loss without distorting the efficient reallocation of workers from contracting to expanding firms. The findings in this paper suggest that, in addition to unemployment benefits that help mitigate the loss of a good job by allowing workers to search longer for a good match, policies that favour retraining and long lasting job placements (e.g., by means of subsidies for retraining workers and work-sharing) can be effective tools to minimize the loss in skills and therefore in wages that follow job loss events.

An important feature that is missing in this work is the consideration of workers' heterogeneity. We know from the literature on earning dynamics that the sources of wage growth can differ for workers in different education groups. For example, Dustmann and Meghir (2005) show that specific capital can be more important for unskilled workers, while general human capital is more reflected in wages of high skilled workers. Therefore, the next step in the research agenda is to estimate the model separately for each education group and identify the specific drivers of wage growth and earning losses for different type of workers. This would allow to design more effective labour market policies targeted to each sub-group of workers.

2.6 Figures

Figure 2.1 – Timing of events: Unemployed Workers

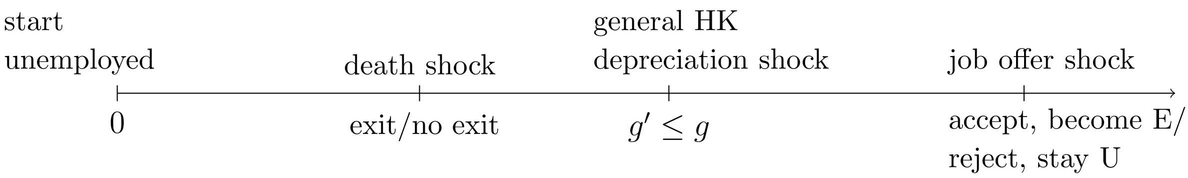


Figure 2.2 – Timing of events: Employed Workers

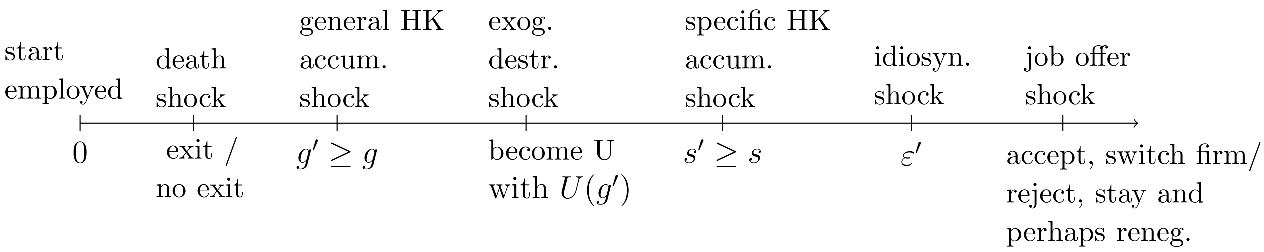
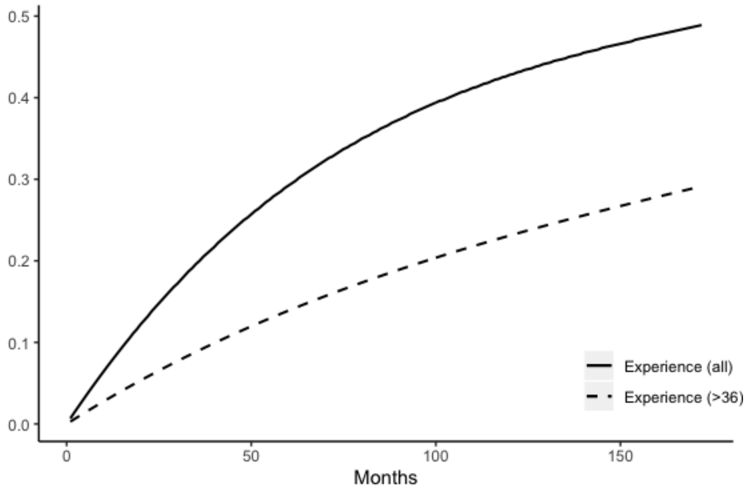


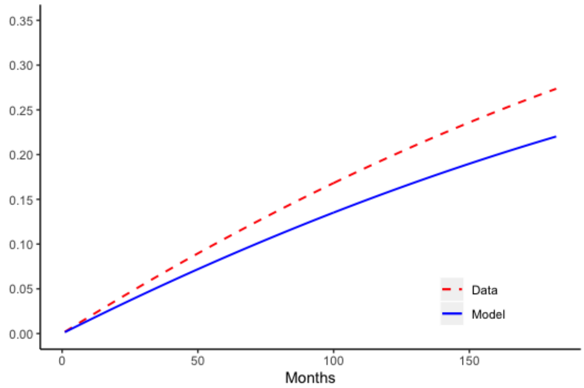
Figure 2.3 – Returns to Experience in the SIAB-7514 dataset



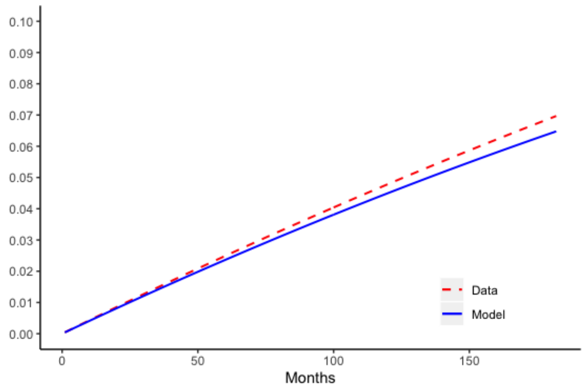
Source: Author's calculation on the SIAB 7514 data

Notes: Returns to experience for workers' total career (continuous line) are computed fitting a fourth order polynomial in experience, controlling for tenure, and including individual, time and firms fixed effects, calculated as in Lamadon, Manresa, and Bonhomme, 2016. Returns to experience for workers' career truncated at year 3 (dashed line) are computed similarly, but including dummies for the first three years of experience, to capture the different slope of the returns in the two time periods (before and after year three). The lines in the plot are obtained by fitting the fourth order polynomial functions in the two cases.

Figure 2.4 – Returns to Tenure and Experience: Model VS Data



(a) Returns to Experience

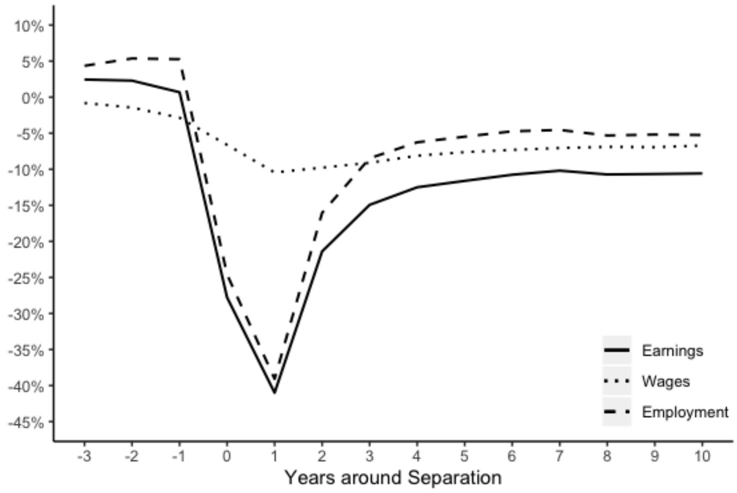


(b) Returns to Tenure

Source: Author's calculation on the SIAB 7514 data.

Notes: Returns to experience and tenure in the model and in the data are obtained estimating equation (2.14). For the data counterpart of returns to experience, only the slope starting from year three of workers' career is considered.

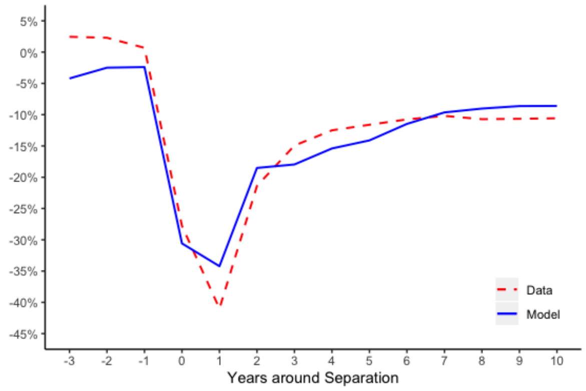
Figure 2.5 – Post-displacement earning and wage losses in the SIAB-7514 dataset



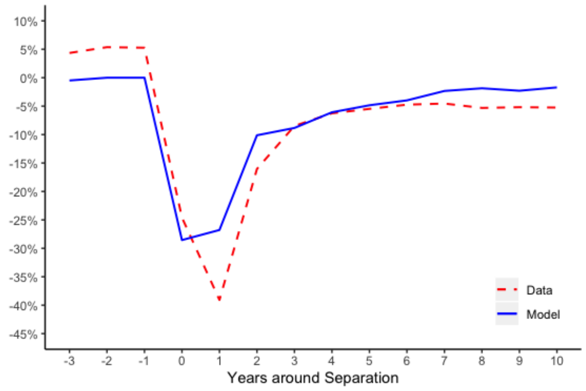
Source: Author's calculation on the SIAB-7514 data

Notes: Post-displacement losses in the data are obtained estimating equation 2.18, using earnings, employment and wages as dependent variable.

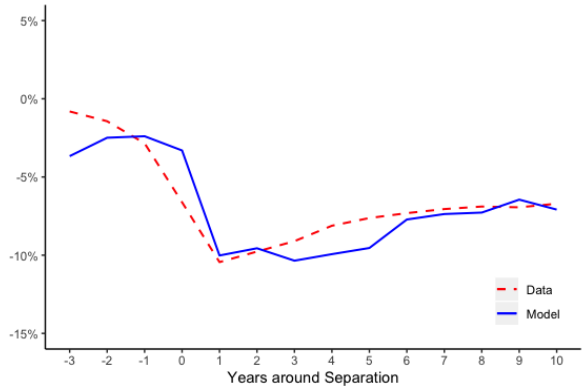
Figure 2.6 – Post-Displacement Losses: Model VS Data



(a) Earnings



(b) Employment



(c) Wages

Source: Author's calculation on the SIAB-7514 data.

Notes: Post-displacement losses in the model and in the data are obtained estimating equation 2.18, using earnings, employment and wages as dependent variable.

Figure 2.7 – Wage Losses Decomposition

Notes: The counterfactual analysis is computed in the following way:

Step 1. I select workers in the treatment group for each separation year y and artificially set the exogenous separation event to 0 to compute the counterfactual series of wages, specific and general human capital for years $t \in (y, y + 10)$.

Step 2. I assign the counterfactual paths of general human capital obtained from Step 1, to the workers in the treatment group and compute the series of average wages for ten years after the separation event. The percentage deviation of this series of wages from the the counterfactual series computed in Step 1 represents the post-displacement wage losses not attributable to the loss in general human capital.

Step 3. I assign the counterfactual paths of both general and specific human capital obtained in Step 1 to the workers in the treatment group and compute the series of average wages for years for ten years after the separation event, to obtain the post-displacement wage losses not attributable to loss in general and specific human capital.

2.7 Tables

Table 2.1 – Model Parameters

Parameters	Description
λ_0	Contact rate during unemployment
λ_1	Contact rate during employment
δ	Exogenous rate of job destruction
σ_ε	Variance of $H(\varepsilon)$ distribution
ρ_ε	Persistence of $H(\varepsilon)$ distribution
σ_θ	Variance of the $F(\theta)$ distribution
$\overline{s}$	Max level of specific human capital
γ	Accumulation rate of specific human capital
$\overline{g}$	Max level of general human capital
ϕ_e	Appreciation rate of general human capital
ϕ_u	Depreciation rate of general human capital
α	Worker bargaining power
p_z	Unemployment payoff

Table 2.2 – Targeted Moments

Targeted Moments	Data	Model
average E–E monthly transition rate	0.009 *(2.13e-05)*	0.010
unemployment rate	0.08	0.09
average E–N monthly transition rate	0.010 *(2.35e-05)*	0.013
average E–N monthly transition rate for 1 year of tenure	0.021 *(4.78e-05)*	0.036
average E–N monthly transition rate for 2 years of tenure	0.011 *(6.22e-05)*	0.014
average E–N monthly transition rate for 3 years of tenure	0.0084 *(7.28e-05)*	0.0076
average E–N monthly transition rate for 4 years of tenure	0.0078 *(8.26e-05)*	0.005
average E–N monthly transition rate for 5 years of tenure	0.0068 *(4.22e-05)*	0.004
variance of log wages, $var(ln(w))$	0.042	0.069
min-mean ratio, $w_0/\overline{w}$	0.739	0.881
coefficient $\hat{\beta}_1$ from regression in eq. (2.14)	0.00043 *(1.76e-06)*	0.00041
coefficient $\hat{\beta}_2$ from regression in eq. (2.14)	-2.59e-07 *(5.99e-09)*	-3.07E-07
coefficient $\hat{\chi}_1$ from regression in eq. (2.14)	0.0019 *(4.09e-06)*	0.0015
coefficient $\hat{\chi}_2$ from regression in eq. (2.14)	-2.18e-06 *(4.47e-09)*	-1.73E-06
coefficient $\hat{\beta}_3$ from regression in eq. (2.15)	-4.35e-05 *(3.72e-07)*	-2.25E-05
coefficient $\hat{\pi}$ from regression in eq. (2.16)	-0.0021 *(4.6e-05)*	-0.0024

Source: Author's calculation on the SIAB-7514 data
Notes: Standard errors in parenthesis.

Table 2.3 – Calibrated Parameters

Parameters	Description	
λ_0	Contact rate during unemployment	0.178
λ_1	Contact rate during employment	0.064
δ	Exogenous rate of job destruction	0.003
σ_ε	S.D. of $H(\varepsilon)$ distribution	0.627
ρ_ε	Persistence of $H(\varepsilon)$ distribution	0.735
σ_θ	S.D. of the $F(\theta)$ distribution	0.061
$\overline{s}$	Max level of specific human capital	1.119
γ	Accumulation rate of specific human capital	0.008
$\overline{g}$	Max level of general human capital	1.147
ϕ_e	Appreciation rate of general human capital	0.023
ϕ_u	Depreciation rate of general human capital	0.059
α	Worker bargaining power	0.774
p_z	Unemployment payoff	1.525

Notes: The parameters are calibrated jointly using the simulated method of moments. Details for the calibration algorithm are explained in Appendix 2.A.2.

Appendix

2.A Numerical Details

2.A.1 Model Solution Details

I solve the model numerically under the assumptions listed in Section 2.3.2. In practice, I solve the Surplus equation (2.10) and the Unemployment value function (2.7) jointly using a contraction mapping on a discretised space for the state variables $(\theta, s, g, \varepsilon)$.

Given that the derivation of an explicit solution for the equilibrium wage is intractable, I derive it numerically. I use a grid for wages and solve the value function for employment described in Equation (2.8) by value function iteration, given the equilibrium functions for the match surplus and unemployment. Then, I obtain the wages by inverting this function using the bisection method to respect the bargaining protocol rules described in section 2.2.2.

Once the model is solved, I then simulate the data at monthly frequency. Specifically, I simulate work histories for 10,000 workers, all born unemployed, and 2,100 periods. I then discard the first 1,500 periods to remove the effects of initial conditions. I compute the moments needed for identification on the remaining 600 periods (50 years). In the simulation, I allow the variables that indicates the fixed component of the firm productivity θ and the time-varying idiosyncratic shock component ε to take values in between the grid points, but not above and below the minimum and maximum values on the grid. Accordingly, I use linear interpolation to find the corresponding values on the surplus and wage functions.

2.A.2 Optimization Details

The calibration of the parameters of interest is done by Simulated Method of Moments. I compute the same set of moments on the true data and on the simulated data and then chose the parameters that minimise the distance between the two vectors, as explained in Section 2.3.3. When in the real data I control for unobserved firm heterogeneity, in the simulated data I explicitly control for the state variable representing the fixed component of the match productivity, θ. The weighting matrix used to solve the optimization problem described in Equation (2.17) is the identity matrix.

The optimization is implemented following the global optimization algorithm suggested in Guvenen *Computational and Empirical Methods for Dynamic Economics* PhD Lecture Notes. The algorithm I use exploits parallel programming and is made of the following steps:

(i) Set iteration $i = 0$;

(ii) Set an initial weight $\omega_i \in [0, 1]$;

(iii) Generate a large number of quasi-random numbers using Sobol sequence;

(iv) Take the first N of these points as initial guesses, $\mathbf{x_j}$ with $j \in \{1, ..., N\}$, and start on N machines a local optimizer (e.g. Nelden-Mead);

(v) After the local optimizer converges on all machines, take the maximum of all the machines $\mathbf{z}^*$ and derive a linear combination of this best point and a new quasi-random number, like $\tilde{\mathbf{x_j}} = \omega_i \mathbf{z}^* + (1 - \omega_i)\mathbf{y_j}$;

(vi) Update iteration $i = i + 1$ and ω_{i+1} and the initial guess $\mathbf{x_j} = \tilde{\mathbf{x_j}}$ for the new local optimization;

(vii) Iterate until convergence.

In practice I set $N = 44$.

2.B Data Work Details

2.B.1 Construction of the Monthly Panel

The SIAB dataset contains information about the employment history of every individual in the sample stored in spell format with given start and end dates that differ for each spell and individual. In order to perform the empirical analysis, I transform the dataset from spell format to monthly format. I do this by choosing the 1st of the month as reference date and attributing the information of the spell to the month if the spell starts before or on the 1st of the month. For example, if the worker is employed full time subject to social security in the spell that goes from the 29th of January until the 15th of March, I assign this information to the months of February and March. The monthly panel is made of 31,214,294 observations.

2.B.2 Variables Definition

The main variables used in the empirical analysis are defined as:

1. *Employment.* A worker is defined to be employed in month t if he/she is employed full time subject to social security on the first day of the month; the worker is considered non-employed in all other cases.

2. *Wages and Earnings.* Wages are recorded only for employed workers, and are considered missing for non-employed workers. Earnings are equal to wages during months of employment and to 0 during months of non-employment.

3. *Job-to-job transition (E-E).* A job-to-job transition is recorded in the following two cases:

   (i) if the worker is employed in firm j in month t and in firm j' in month $t+1$;

   (ii) if the worker is employed in firm j in month t and in firm j' in month $t+2$, and the worker is non-employed and doesn't apply for unemployment benefits in month $t+1$.

4. *Employment-Non Employment (E-N).* An Employment-Non Employment (E-N) transition is recorded in the following two cases:

   (i) when the worker is employed in month t and non-employed and applies for unemployment benefits in month $t+1$;

   (ii) if the worker is employed in month t and non-employed for at least 2 periods.

2.B.3 Construction of the Yearly Panel

Starting from the monthly dataset, I transform the employment, earnings and wages variables in yearly observations by averaging the records across all months during a year. I record a employment-non-employment transition (E-N) and a job-to-job transition (E-E) in a given year, respectively, if at least one E-N or E-E transition is observed in the monthly panel in that year. I consider the annual employer the establishment in which the worker is employed in January of the corresponding year. The yearly panel is made of 2,059,342 observations.

2.C Unobserved Firm Heterogeneity

To discipline firm heterogeneity, I follow the recent literature based on the work by Lamadon, Manresa, and Bonhomme (2016) and classify firms using tools from machine learning. In particular, I cluster firms based on their wage distribution using k-means algorithms and use the obtained clusters as firms' type, which I use as controls in the wage and job-to-job transitions regressions (2.14) and (2.15). The idea is that variation in the firms' wage distribution conveys information about the permanent firm type.

In practice, I use the information on average wages paid by firm to full time workers, reported in the establishment side of the dataset, and classify firms in groups using k-means algorithm.[20] This classification procedure is a standard clustering method, which solves for the best partition of the data according to the following objective function:

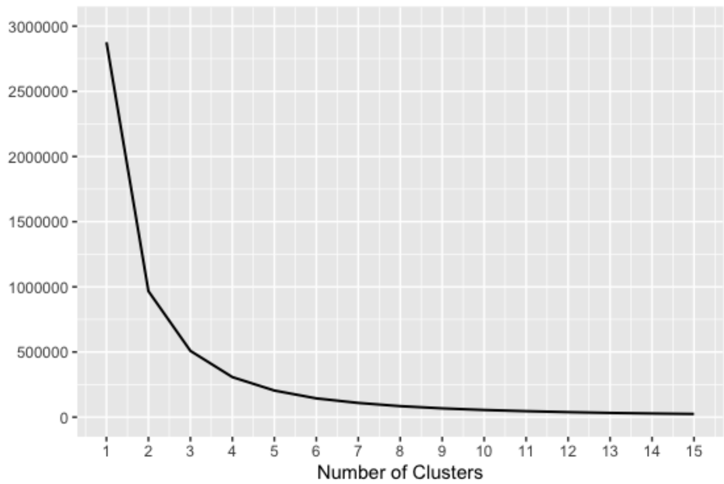
$$\underset{\tilde{h},k_1...k_n}{\operatorname{argmin}} \sum_{i=1}^{N} \|\hat{h_i} - \tilde{h}(k_i)\|^2 \tag{2.20}$$

where, N represents the sample size; $k_i \in 1, ..., K$ represent the partitions of the observations $\{1, ..., N\}$ with $1 < K \leq N$; $\hat{h}_i$ is a vector of features used for classification, which in my case is the average wage paid the establishment, and $\tilde{h}(k_i)$ represents the vector of the selected data features for group k to which i is assigned, whose elements are computed as averages over the group members. The solution of equation (2.20) is a mapping of each i into a cluster k, such that the squared Euclidean distance between the vector of characteristics $\hat{h}_i$ and the average characteristics in the corresponding group are minimized.

To implement this classification it is necessary to chose the number of classes. In order to do so, I compute a measure of fit for the k-means as a function of the number of clusters and I find that improvements in fit appear to flatten out after about five-six clusters. This is shown in Figure 2.C.1, where I report the total within sum of square as a function of the number of clusters. Therefore I set the number of cluster to 5.

[20]More specifically, I use the residual of a regression of firms' average wages on year dummies to net out the time variation.

Figure 2.C.1 – Change in k-means fit with number of clusters



Source: Author's calculation on the SIAB-7514 data

Notes: The figure shows a measure of fit for k-means, the total within sum of squares, as the number of clusters increases.

References

Altonji, Joseph G., Anthony A. Smith Jr., and Ivan Vidangos (2013). “Modeling Earnings Dynamics”. In: *Econometrica* 81.4, pp. 1395–1454.

Bagger, Jesper, François Fontaine, Fabien Postel-Vinay, and Jean-Marc Robin (2014). “Tenure, Experience, Human Capital, and Wages: A Tractable Equilibrium Search Model of Wage Dynamics”. In: *American Economic Review* 104.6, pp. 1551–96.

Burdett, Ken, Carlos Carrillo-Tudela, and Melvyn Coles (2020). “The Cost of Job Loss”. In: *The Review of Economic Studies, forthcoming.*

Burdett, Kenneth and Dale Mortensen (1998). “Wage Differentials, Employer Size, and Unemployment”. In: *International Economic Review* 39.2, pp. 257–73.

Cahuc, Pierre, Fabien Postel-Vinay, and Jean-Marc Robin (2006). “Wage Bargaining with On-the-Job Search: Theory and Evidence”. In: *Econometrica* 74.2, pp. 323–364.

Davis, Steven J and Till M von Wachter (2011). “Recessions and the Cost of Job Loss”. In: *Brookings Papers on Economic Activity* 43.2, pp. 1–72.

Dustmann, Christian and Costas Meghir (2005). “Wages, Experience and Seniority”. In: *The Review of Economic Studies* 72.1, pp. 77–108.

Fitzenberger, Bernd, Aderonke Osikominu, and Robert Völter (2005). “Imputation rules to improve the education variable in the IAB employment subsample.” In: *FDZ-Methodenreport, 03/2005 (en)* 83.

Huckfeldt, Christopher (2018). *Understanding the Scarring Effect of Recessions.* 2018 Meeting Papers 1207. Society for Economic Dynamics.

Jarosch, Gregor (2015). *Searching for Job Security and the Consequences of Job Loss.* Mimeo. University of Chicago, USA.

Jung, Philip and Moritz Kuhn (2018). “Earnings Losses and Labor Mobility Over the Life Cycle”. In: *Journal of the European Economic Association* 17.3, pp. 678–724.

Krolikowski, Pawel (2017). “Job Ladders and Earnings of Displaced Workers”. In: *American Economic Journal: Macroeconomics* 9.2, pp. 1–31.

Lamadon, Thibaut, Elena Manresa, and Stephane Bonhomme (2016). *Discretizing Unobserved Heterogeneity.* 2016 Meeting Papers 1536. Society for Economic Dynamics.

Lazear, Edward P. (2009). “Firm-Specific Human Capital: A Skill-Weights Approach”. In: *Journal of Political Economy* 117.5, pp. 914–940.

Ljungqvist, Lars and Thomas Sargent (1998). “The European Unemployment Dilemma”. In: *Journal of Political Economy* 106.3, pp. 514–550.

MacLeod, W and James M Malcomson (1993). "Investments, Holdup, and the Form of Market Contracts." In: *American Economic Review* 83.

Mortensen, Dale and Christopher A. Pissarides (1994). "Job Creation and Job Destruction in the Theory of Unemployment". In: *Review of Economic Studies* 61.3, pp. 397–415.

Postel-Vinay, F and J-M Robin (2002). "Equilibrium Wage Dispersion with Worker and Employer Heterogeneity". In: *Econometrica* 70 (6), pp. 2295 –2350.

Postel-Vinay, Fabien and Hélène Turon (2010). "On-The-Job Search, Productivity Shocks, And The Individual Earnings Process". In: *International Economic Review* 51.3, pp. 599–629.

Rouwenhorst, G. (1995). "Asset Pricing Implications of Equilibrium Business Cycle Models". In: *Frontiers of Business Cycle Research, Princeton University Press.* Pp. 294–330.

Schmieder, Johannes F., Till von Wachter, and Joerg Heining (2018). *The Costs of Job Displacement over the Business Cycle and Its Sources: Evidence from Germany.* Mimeo. Institute for Employment Research, Nuremberg, Germany.

Topel, Robert (1990). "Specific capital and unemployment: Measuring the costs and consequences of job loss". In: *Carnegie-Rochester Conference Series on Public Policy* 33.1, pp. 181–214.

Yamaguchi, Shintaro (2010). "Job Search, Bargaining, and Wage Dynamics". In: *Journal of Labor Economics* 28.3, pp. 595–631.

Chapter 3

Export, Female Comparative Advantage and the Gender Wage Gap

3.1 Introduction

Over the last decades, the increase in income inequality and the persistence of wage differentials between men and women have been among the main concerns for both policy makers and the public opinion. At the same time, globalisation has been recognised as an important factor behind the widening of the income distribution. While researchers have studied in isolation the determinants of the gender wage gap (see for example Olivetti and Petrongolo, 2016, for a survey) and the effects of trade on wage inequality, especially stemming from workers' skills and firms' characteristics (see Helpman, 2018, for a survey), little attention has been paid to the potential effects of trade on gender wage differentials.[1]

Our paper contributes to fill this gap by first estimating the effect of export activity on the gender wage gap at the firm-worker level, and then by showing that the results are consistent with gender-specific comparative advantage.

To perform the analysis, we use a uniquely rich employer-employee dataset provided by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA), matching social security data on all German private-sector workers with survey data on firms' establishments.[2] The database provides us information on the value of plants' total sales, the share of export on total sales and their

[1] Among the few existing exceptions are Juhn, Ujhelyi, and Villegas-Sanchez (2014), Sauré and Zoabi (2014), and Bøler, Javorcik, and Ulltveit-Moe (2018).

[2] Although our unit of observation is an establishment, henceforth, we will refer to establishments and firms interchangeably.

workforce, in addition to location and sector. It also includes very detailed data on individual workers' wages and benefit receipts, occupation, gender, age, education and experience. The sample comprises yearly observations for over 3.6 million German workers matched with nearly 15,000 establishments from both manufacturing and service sectors, followed from 1993 to 2007.

At the heart of our empirical exercise lies the estimation of a wage equation where, in addition to standard firm's and worker's characteristics, we control for firm's export intensity, its interaction with a dummy for female workers and firm-worker fixed effects.[3] This specification allows us to study how the wage of any given employee reacts to an increase in their firm's export, and to what extent the response is different if the employee is a woman. This tight identification strategy purges from the coefficients any effect of export on workers' selection within the firm, and at the same time alleviates concerns of endogeneity of export with respect to wages and employment composition, since it is unlikely that any single worker may affect firm's sales abroad. Additionally, controlling for state-time, sector-time and (in the most demanding specifications) for firm-time fixed effects allows us to address the potential simultaneity bias arising from confounders that may affect both export and the wage trajectory of workers.

Our first set of results, obtained on the full sample, suggest that export does not affect on average the wages of male and female employees. We then dig deeper and study whether this masks heterogeneity across occupations. Interestingly, we obtain strong evidence that an increase in firm's export significantly reduces the wage of female blue collar employees relative to their male co-workers (thereby widening the gender wage gap), while it increases the wage of female white collars relative to their male peers (thereby narrowing the gap). This result proves robust also to controlling for firm's sales, whose effect on the gender wage gap is quite muted relative to that of export.

The fact that the gender wage gap reacts more to export than domestic sales suggests that selling to foreign markets may require the firm to change the intensity in the use of certain skills in a way that makes women relatively more demanded in non-production tasks. This resounds with the existing evidence that women tend to have a comparative advantage in performing white collar tasks, especially those intensive in interpersonal relations and in the use of computers, while they have a disadvantage in blue collar, "brawn"-intensive occupations (see for example Spitz-Oener, 2006; Black and Spitz-Oener, 2010; Borghans, Weel, and Weinberg, 2014; Ngai and Petrongolo, 2017; Cortes, Jaimovich, and Siu, 2018). If export

[3] As it will be clearer, we focus on the export share because our sample exhibits a substantial within-firm variation in this variable and a very limited one in the export status.

requires a more intensive use of “male” skills in production (e.g., because it changes the production line in a way that calls for more “brawn”), and of “female” skills in non-production tasks (e.g., because it takes more ability in interpersonal relations to deal with foreign customers), an expansion in foreign activities will increase (decrease) the demand for females in white-collar (blue-collar) occupations and their wages.

While our evidence is consistent with this hypothesis, we further assess its validity by proceeding in three steps. First, we estimate how export correlates with the share of women in white collar and blue collar employees at the firm level. Consistently, our results highlight a positive association between firms' export and the share of female employees in white collar occupations, while no significant correlation can be established for blue collars.

Next, we assess whether increasing export induces the firm to reward through promotion female white collars more than their male colleagues. To this end, we estimate a linear probability model for promotion at the firm-worker level and show that an increase in firm's export slightly raises the probability that any of its female white collar be promoted compared to male employees in the same occupations.

Finally, we take a step further and study whether the reduction in the gender wage gap for white collar workers is driven by those performing tasks related to female comparative advantage, such as the non-routine interactive ones. Similarly, we investigate if the widening in the gap for blue collars is more pronounced for those employees in female comparative disadvantage tasks, such as the routine manual ones. In both cases, the estimation of our baseline specifications on the sub-samples for different types of tasks corroborates the hypothesis that gender-specific comparative advantage drives the effect of exports on wages.

In the final section of the paper, we perform robustness analysis showing that our results are not driven by the censoring of wage data up to a social contribution limit, or by recently hired workers, which may have been selected by the firm in order to improve export performance.

Our paper makes a number of novel contributions. It is the first, to our knowledge, to show that export widens the gap between male and female blue collar workers while it reduces it among white collars. The closest paper to ours is Bøler, Javorcik, and Ulltveit-Moe (2018), who use a similar identification strategy on Norwegian matched employer-employee data. They find, however, that export increases the wage differentials between men and women, without distinguishing between white and blue collar workers. Their explanation is that export requires flexibility in working hours, and hence it penalises women because they are typically more constrained by family duties. This hypothesis is consistent with our proposed mechanism of export reinforcing female comparative (dis)advantage, which in their case stems from time flexibility.

More importantly, we probe deeper into the mechanism behind the heterogeneous effects of export on the gender wage gap and study whether this is due to female comparative advantage in tasks that are key when firms serve a foreign market. In particular, we show comparative advantage of women in interactive tasks to drive their wages up both in absolute term and relative to men, while comparative disadvantage in routine manual occupations pushes female wages down, thereby widening the gap with male co-workers. We are aware of two papers studying how trade may affect the gender wage gap in presence of female comparative advantage. Saure and Zoabi (2014) mainly address this issue theoretically and provide evidence based on U.S. export to Mexico in 58 sectors suggesting that trade may increase the gender wage gap. Juhn, Ujhelyi, and Villegas-Sanchez (2014) use firm-level data from Mexico showing that export, combined with technological upgrading, contributed to reduce the gap between male and female blue collar workers. The latter work is closer to ours, although it differs in a number of aspects, from the country of analysis to the identification strategy (within firm instead of within firm-worker variation). More importantly, we study more in detail comparative advantage at the task level.

This paper is related to three main strands of work in international trade and gender economics. An established literature has shown that trade, by inducing reallocations across sectors and firms, is in part responsible for the increase in the skill premium (see, among others, Stolper and Samuelson, 1941; Epifani and Gancia, 2008) and in the component of wage inequality stemming from firms' characteristics and sorting (see, among others, Helpman, Itskhoki, and Redding, 2010; Amiti and Davis, 2012; Bonfiglioli, Crinò, and Gancia, 2018). Recently, a few papers have studied whether trade may affect inequality by widening or narrowing the gender wage gap (see Juhn, Ujhelyi and Villegas-Sanchez, 2014, Saure and Zoaby, 2014, and Bøler, Javorcik and Ulltveit-Moe, 2018). Yet, the evidence is mixed and the mechanism behind this link remains largely an open question. Our analysis contributes to the understanding of the role of gender-based comparative advantage in trade and income inequality and identifies it at the task level. An important implication of our results is that higher female labour participation, may increase a country's export because selling to foreign markets is intensive in tasks for which women have a comparative advantage.

A growing literature in gender economics has shown that women have a comparative advantage in occupations entailing non-routine interactive and analytical tasks (see Black and Spitz-Oener, 2010; Cortes, Jaimovich, and Siu, 2018), which, combined with the structural transformation towards services and technological change, have contributed to reduce the gender wage gap (see Olivetti and Petrongolo, 2016, and references therein). Our results suggest that also globalisation, combined with female comparative advantage, may have narrowed wage differentials between men and women, especially among non-production workers.

Related contributions in the same literature have also documented that women have worse career prospects than men and that over one half of the gender gap in life-time earnings is attributable to wage dynamics within the firm (see Goldin, 2014). Several explanations to this phenomenon have been put forward, including sorting into different type of firms, differences in productivity, bargaining power, frictions in the labour market (Card, Cardoso, and Kline, 2015). Our results suggest that the rise in export at the firm level may significantly contribute to the reduction of this gap, especially for women in white collar occupations.

The remainder of the paper is organised as follows. Section 2 describes the employer-employee matched data used in the analysis and provides statistics on the gender and sectoral composition of our sample. In Section 3, we explain our empirical approach and the baseline results on the effect of export on the gender wage gap, first in general and then by occupations, highlighting the heterogeneous effects across white and blue collar workers. Section 4 explores the mechanism related to female comparative advantage. In Section 5, we perform a series of robustness checks. Section 6 concludes.

3.2 Data Description

Our study is based on the LIAB matched employer-employee dataset provided by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB). The LIAB dataset combines information on individuals, from the Integrated Employment Biographies (IEB) dataset, and on establishments, from the IAB Establishment Panel.[4]

The data on individuals cover all workers, trainees, job-seekers and benefits recipients, subject to social security any time in the period that goes from 1975 to 2014, excluding only civil servant and self-employed. The dataset contains detailed information on the workers' employment status (employed, non-employed), type of contract (full-time, part-time), occupation category classified according to the "Classification of Occupations 2010" (KldB2010) with 3 digit level of detail, (daily) wages up to a contribution limit and benefit receipts. Basic biographic

[4]Specifically, we use the up-to-date version of the dataset, called *LIAB-QM2-9314*.

information, like gender, age and education level of the workers, is also included. Additionally, the dataset reports the record of the workers' establishment identifier, along with some general information on the geographic location, sector of activity classified according to the standard NACE Rev.2 classification with 3-digit level of detail, median wage and basic employment structure characteristics (e.g number of full-time workers, part-time workers).

The IAB Establishment Panel is constructed from a yearly longitudinal survey based on a random sample of establishments with at least one employee liable to social security, stratified according to industry, federal state, and firm size.[5] The survey started in 1993 in West Germany, covering 4,265 plants, which account for 0.27% of all plants in western Germany and 11% of total employment. In 1996 it was expanded to East Germany, and currently it covers approximately 16,000 establishments.[6] The survey was conducted to provide the Federal Employment Agency with information on the demand side of the labour market. For this reason the dataset includes detailed information on the workforce composition, its characteristics and development over time. Additionally, it has rich information on business and investment activities, including the value of total sales and share of export on total sales, along with general information about the plant (e.g. age, location, industry).

The *LIAB* matched employer-employee data set is then created by linking information on plants and workers through the establishment identifier, available in both datasets. Specifically, all individuals from the IEB that have been employed in one of the IAB Establishment Panel plants on the 30th of June are selected to form the *LIAB* dataset. These individuals are followed throughout the sample period and all their records at the 30th of June of every year is made available. The linked dataset includes 60,124 establishment, ranging from 4,188 to 15,061 per year, and 11,581,550 workers, ranging from 1,592,874 to 2,536,470 per year.

3.2.1 Estimation Sample

In LIAB, the largest connected set of individuals and establishments with information on the export activity refers to West-Germany in the years 1993-2007. For this reason, we only focus our study on this area and this time span. We further

[5]The sample is disproportionately stratified. To correct for this issue, we follow the advice of the FDZ data centre and use controls for industry, federal state and firm size in the panel analysis.

[6]The unit of record of the dataset is the establishment. Notice that in the empirical analysis we use the word firm and establishment interchangeably.

restrict the sample to 18-54 years old workers and to establishments with more than five employees. In case of multiple identical employment spells for the same worker in the same year, we keep the episode with the highest wage, and drop spells with wages below 10 Euros (in 2010 prices).

After applying these sample selection rules, we are left with a sample of 14,955 firms and 3,603,167 workers followed from 1993 to 2007, which we use in our econometric analysis.

One limitation of the dataset is the lack of information on hours worked. Following common practice, we tackle this issue by only considering workers employed full time subject to social security as employed.

3.2.2 Descriptive Statistics

Table 3.1 reports some descriptive statistics on firms' export activity in both the firm-level dataset (IAB Establishment Panel) and in the matched employer-employee data (LIAB) that we use in the analysis. In line with the national statistics, our calculations on the firm level IAB Establishment Panel, comprising 65,180 firms in the time period that goes from 1993 to 2010, show that 22% of the firms in the sample are exporters, and that the average fraction of sales from export activity relative to the total sales is equal to 7%. These statistics are much higher when computed on the LIAB matched dataset. Specifically, in the LIAB dataset 33% of firms are classified as exporters and the share of export on total sales is 31%, and exporting firms employ 68% of the total workforce. This indicates that exporting firms are larger and, therefore, are connected to more employees in the linked sample.

Furthermore, the data show that the establishment's decision to export is a long term one and defines the firm throughout the whole sample. In fact, only 5% of all firms switch status from exporter to non-exporter or viceversa, and on average firms that switch status do it only 1.9 times.

Some additional basic descriptive statistics for exporting and non-exporting firms computed on the LIAB dataset are reported in Table 3.2. Here, we also distinguish by male and female workers.

In line with the literature, our calculations show that on average exporting firms are larger, have higher volume of sales, and pay higher wages relative to non exporting firms (see for example Bernard et al., 2007).

Additionally, the gender wage gap is slightly higher in non-exporting firms, where unconditionally, women are paid 25% less than men. In exporting firms the gap is still high and equal to 23%.

Exporting and non-exporting firms employ workers with similar characteristics, in terms of age and experience, and exporters employ slightly more educated workers. We can see that the majority of workers in our sample are medium skilled, both in exporting and non-exporting firms and that there are no striking differences between male and female workers' levels of education.[7]

When both manufacturing and service sectors are considered in the sample, the share of white collar workers in non-exporting firms is 40% and 28% in exporting firms. However, going beyond this table, the share of white collar workers in non-exporting firms drops to 26% if we do not consider services. As expected, the service sector is in fact less export oriented and it employs more female workers. We can clearly see this in Figure 3.1 and 3.2, where we respectively report the share of exporting firms and of female workers by sector of activity at the 2 digit level of detail according to the NACE Rev.2 classification of activity. Industries in the manufacturing sector are marked in blue while industries in services in red. In fact, there is a significant disproportion between the two sectors in terms of export activity. In particular, on average, in the manufacturing sector 74% of firms exports, while in services only 18%. Additionally, the average share of female workers in the manufacturing sector is 25% while in services it is 40%. Furthermore, as expected for the German economy, the most export-oriented sector is the motor vehicles in the group of manufacturing, while within the group of services most of exporting firms are in engineering activities.

Considering the whole sample, non-exporting firms employ more women than exporting firms, respectively equal to 25% and 18%. As before, this is due to the fact that most of firms in the service sector, which employ on average more women, are included in the sample of non-exporting firms. If we drop services from the sample, the share of women in non-exporting firms becomes closer to the share of women in exporting firms and specifically equal to 17%. Additionally, considering the whole sample, most of women work in white collar occupations, where they occupy 72% and 46% of white collar positions in domestic and exporting firms, respectively.

As we have seen, several differences between exporting and domestic firms in terms of workforce composition emerge mostly because of heterogeneity across service and manufacturing industries. In spite of this evidence, in this study we decide to use the full sample that includes both manufacturing and service industries. This choice is motivated by our identification strategy, which is based on exploiting variation of firms' export activity and (relative) wages within sectors,

[7]We define low skill the workers with no vocational training, medium skill the workers with vocational training and high skill the workers with university degree.

firms and matches.[8] A detailed explanation of this is given in the next sections.

3.3 Export and Gender Wage Gap: Empirical Evidence

In this section we first explore how firm's export activity affects wage differentials between men and women in general, and then we investigate whether it has heterogeneous impact on different groups of workers. We will specifically focus on white versus blue collar workers, given that they engage in very different sets of tasks (for example "brawn" versus "brain" intensive tasks), that can be of different use to the firm when it decides to expand its sales on international markets.

In our main specifications, we identify the correlation between firms' export and gender wage gap by exploiting variation of wages for any given worker who remains employed in the firm as its export intensity varies over time, and by controlling for possible firm-year specific shocks that can simultaneously affect export decisions and wages. As we will argue below, this strategy conceivably allows us to capture the causal effect of export on the gender wage gap. Moreover, with one of our specifications we are also able to quantify and compare the elasticities of the gender wage gap to firms' export sales and domestic sales.

3.3.1 The Baseline Estimation Strategy

We analyse the effects of firms' export activity on the gender wage gap in the German labour market by looking at the *within employer-employee matches* dynamics. In doing so we depart from most empirical works that study this relation at the industry and firm level.[9] In practice, we adopt a similar approach to Bøler, Javorcik, and Ulltveit-Moe (2018), and estimate the following wage equation:

$$\ln w_{ijst} = \beta_1 Exp_{jt} + \beta_2 fem_i * Exp_{jt} + \mathbf{C}'_{it}\pi_1 + \mathbf{F}'_{jt}\pi_2 + \eta_{st} + \eta_{ij} + \varepsilon_{ijst} \quad (3.1)$$

where w_{ijst} is the gross daily wage of worker i, employed by firm j in sector s and year t. The variable fem_i is a dummy variable indicating whether individual i is female, and Exp_{jt} indicates the export activity of firm j at time t (alternatively, the export share or the log of export value). Equation (3.1) controls for a vector

[8] We also perform the whole analysis restricting our sample to the manufacturing sector with no significant differences.

[9] See for example Ozler (2000), Black and Brainerd (2004), Ederington, Minier, and Troske (2009) and Juhn, Ujhelyi, and Villegas-Sanchez (2014) among others.

of worker's characteristics $\mathbf{C}'_{it}$, including nationality, experience, its square, and occupation, and for a vector of firm's characteristics $\mathbf{F}'_{jt}$ including (log of) firm size and geographic location.

Further, we control for sector-year fixed effects, η_{st}, to account for systematic variation in wages across sectors in any given year. This makes sure that we compare wages within each industry and time, so that the estimate of the coefficient of interest that measures the effect of export on the gender wage gap, $\hat{\beta}_2$, is not driven by selection into industry. This could matter in case exporting firms were more (or less) concentrated in "male-intensive" industries.

Match fixed effects are denoted by η_{ij}, and allow us to exploit a finer source of variation given by the change in the firms' export activity, holding constant the within-firm workforce gender composition. In this specification, the estimated coefficient $\hat{\beta}_2$ captures the effect of time variation in firms' export activity on the relative wage of a specific female-male couple of workers employed in the firm. By holding the firms' workforce composition constant, the estimation of the effect of export on gender wage gap is less likely to be biased by endogenous mobility and assortative matching issues, which would arise if the firm selects higher ability workers as it intensifies export (Helpman, Itskhoki, and Redding, 2010). The within-match identification also reduces possible bias due to reverse causality. It is in fact less likely that the main driver of firms' export is the ability of specific workers.

Notice that in this specification we cannot quantify the total gender wage gap, since the variable fem_i is collinear with the fixed effect η_{ij} and therefore the parameter associated to it cannot be estimated. However, the results from estimating (3.1) with firm instead of match fixed effects, reported in Table C1 of Appendix C, allow us to quantify the firm-level gender wage gap at around 20 per cent.

One issue with the model above is that it doesn't take into account the possibility of firm-specific productivity shocks that may affect both export decisions and the demand for male and female workers. Thus, in the next specifications we attempt to control for this possible source of bias in two ways. First, by including the (log of) total firms' sales and its interaction with the female dummy as additional proxy for firm heterogeneity in productivity. Second, by controlling for firm-year fixed effects, η_{jt}, to absorb elements of unobserved heterogeneity that may drive selection of firms into exporting. These two extended models are specified in equations (3.2) and (3.3):[10]

$$\begin{aligned}\ln w_{ijst} =&\gamma_1 Exp_{jt} + \gamma_2 fem * Exp_{jt} + \mathbf{C}'_{it}\mu_1 + \mathbf{F}'_{jt}\mu_2 + \\ &\nu_1 \ln S_{jt} + \nu_2 fem * \ln S_{jt} + \eta_{st} + \eta_{ij} + \varepsilon_{ijst}\end{aligned} \tag{3.2}$$

$$\ln w_{ijst} = \delta_1 fem_i * Exp_{jt} + \mathbf{C}'_{it}\varrho_1 + \mathbf{F}'_{jt}\varrho_2 + \eta_{jt} + \eta_{ij} + \varepsilon_{ijst} \tag{3.3}$$

where the variable S_{jt} indicates total sales of firm j at time t.

The drawback of specification (3.3) is that it only allows us to estimate the effect on the gender wage gap, but not on the overall wages of male and female workers, since both time-invariant individual characteristics (such as female dummy) and time variant firm characteristics (such as export) are subsumed by the new fixed effect.

In order to account for correlation across workers within firm over time, we cluster standard errors by firm in all specifications.

Results of the Baseline Estimation

The estimation results are reported in Table 3.3. Specifically, in column (1) we report the estimated coefficients for model (3.1), while in column (2), (3) and (4) we report the results for the model extended to include controls for firms' sales only, its interaction with the female dummy, and firm-year fixed effects, respectively.

Given that our baseline specifications exploit variation of export and wages within-firm and within-match, we proxy firms' export activity with its export share rather than a dummy for export status, which exhibits too little time variation to allow for identification, as shown in Table 3.1.[11]

The estimation of the baseline model (3.1) shows that, when the gender composition of the workforce is held constant, an increase in firms' export share does not have a significant impact on workers' wages. A one percentage point increase in export share is associated to an increase of 0.0028% in wages of male employees (coefficient $\hat{\beta}_1$) and to a 0.0018% increase in the relative wage of female employees (coefficient $\hat{\beta}_2$), but these coefficients are not statistically significant.[12] Controlling for firms' sales as a proxy for firms' productivity further reduces the

[10] Since we cannot observe firms that change sector of activity within the year, the firm-year fixed effects, η_{jt}, substitute the sector-year fixed effects, η_{st} in model (3.3).

[11] Precisely, the independent variable is share of export on firm's total sales and lies in a $[0, 1]$ interval. Given that the model is log-linear, the correct interpretation of the coefficients of interest is a semi-elasticity.

[12] Given that the model is log-linear, the coefficients $\hat{\beta}_1$ (and $\hat{\beta}_2$) represents a semi-elasticity. Thus, it is interpreted as *a unit change in the export share* is associated to a $\hat{\beta}_1 \times 100$ % change in wages. Given that a unit change in export share represents a 100% change, we divide the estimated coefficient by 100 to obtain a more meaningful interpretation.

magnitude of these coefficients (columns (2) and (3)). An increase in firms' sales, however, seems to have a small but positive effect on the wages of male workers, specifically equal to a 0.009% rise in their salary following a 1% expansion, while it still shows no effect on the relative wages of female employees. Finally, the results from the estimation of model (3.3) confirm the absence of a significant effect of export on the gender wage gap.

In all specifications, the results of the estimation of the rest of the control variables are in line with the literature. The linear and quadratic terms of labour market experience have a significant effect on wages, which is increasing at decreasing rates. White collar workers earn on average 2.6% higher wages relative to their blue collar colleagues, and larger firms exhibit a wage premium of roughly 2.3%.

In conclusion, our specification reveals that firms' export activity does not have a significant impact on workers' wages, once we control for the gender composition of the workforce. In the next section we explore the possibility that this lack of significant results may mask heterogeneity in the effects of export activity on the gender wage gap depending on workers' occupation as white or blue collars.[13]

3.3.2 Heterogeneous Effects by Occupation

In this section, we explore whether firms' export affects the relative wage of female blue collar workers differently from that of female white collars. We address this heterogeneity in two ways. First, we focus on the within-match specification and estimate model (3.1), (3.2) and (3.3) described in Section 3.3.1 separately on the sample of white collar and blue collar workers.

Then, we build a model that enables us to directly draw conclusions on the differential impact of firms' export on the two occupational groups of workers, both qualitatively and quantitatively, and to test whether it is statistically significant. Our proposed strategy is to extend the within-match specification explained in equation (3.1) by adding a triple interaction term between a dummy variable that defines white collar workers denoted as wc_i, the export variable and a dummy variable for female workers.

[13] We prefer the occupation classification to the education classification of the workforce because, as we could see in Table 3.2, in the German system there is no clear distinction between high and low skilled workers. Most of the workers have vocational training (64%) and this allows them to work in both white and blue collar occupations.

The model is the following:

$$\ln w_{ijst} = \epsilon_1 Exp_{jt} + \epsilon_2 fem_i * Exp_{jt} + \epsilon_3 wc_i * Exp_{jt} + \epsilon_4 fem_i * wc_i * Exp_{jt} + \mathbf{C}'_{it}\tau_1 + \mathbf{F}'_{jt}\tau_2 + \eta_{st} + \eta_{ij} + \varepsilon_{ijst} \tag{3.4}$$

As in Section 3.3.1, the main source of identification is given by changes in wages of workers that remain within the same firm as it varies its export share throughout time. This enables us to obtain an estimate of the effect of export on the gender wage gap across different occupation groups which is not biased by workers' selection into export-oriented firms.

As before, the specification described in equation (3.4) does not allow us to estimate the total gender wage gap because the marginal effects on time-invariant variables, like female and white collar dummies and their interaction, are subsumed by the match fixed effects.[14] Nevertheless, it gives us relevant information on the differential effects of export on the gender wage gap for the two groups of workers. The coefficients reported in Table C2, however return a gap of 19.1 and 19.9 percent, respectively for blue and white collar femal employees, respectively.

The most informative coefficients for our study are ϵ_2 and $(\epsilon_2 + \epsilon_4)$, which give us information on the effect of export on the (complementary of the) gender wage gap among blue collars and white collars, respectively. Additionally, relevant information is given by the coefficient on the export variable, ϵ_1, which is the export wage premium for blue collar male workers, and the sum of ϵ_1 and ϵ_2, that give us the (absolute) export wage premium for blue collar female workers. Similarly, the export wage premium for white collar male workers is given by the sum of ϵ_1 and ϵ_3, while the sum of the four coefficients, $\epsilon_1 + \epsilon_2 + \epsilon_3 + \epsilon_4$, informs us about the export wage premium for white collar female workers.

In the same spirit of what we do in Section 3.3.1, in order to make sure that these estimates are not affected by other firms' characteristics that may simultaneously affect both export decisions and wages, we also estimate model (3.4) including additional observable and unobservable controls for firm productivity, specifically firms' sales and firm-year fixed effects. In the latter we are only able to estimate the coefficient on the triple interaction term, $fem * white * Exp$, since the rest of the coefficients are collinear with the fixed effects. Thus, we can only draw conclusions on the differential impact of trade on the gender wage gap on white collar workers relative to blue collars.

[14] We drop observations of workers that switch occupation throughout time to have a clearer identification of the effect of export on gender wage for white and blue collars. The percentage of occupation switches in the sample used for the estimation is 3%.

As before, we use the export share of total sales to measure firms' export activity. This implies that the estimated coefficients can be interpreted as semi-elasticities of the gender wage gap to variation in the firms' export share, holding constant the firms' workforce composition, and firms' total sales and firms' unobservable characteristics in the extensions of model (3.4). Additionally, we estimate model (3.1), (3.2) and (3.3) separately on the sample of white collar and blue collar workers and model (3.4) replacing the export share variable with (the *log* of) sales from export, controlling for (the *log* of) domestic sales. We do this to have a clear and direct estimate of the elasticity of wages and gender wage gap to export and domestic sales across occupations. Since this only allows us to look at these relations for the sub-sample of exporting firms (with positive share of export), for comparability we also estimate the effect of export share on the gender wage gap on this restricted sample of firms.

Export and the Gender Wage Gap by Occupation: Results

The results of the estimation of model (3.1), (3.2) and (3.3) on the different groups of blue collar and white collars are reported in Table 3.4.

The first specification reveals that one percentage point increase in the firms' export share positively affects the gender wage gap among blue collar workers by 0.016%, and it does not have a significant effect on the wages of blue collar male workers. The coefficient on the interaction term $Female * Export$ remains negative and significant at the 1% and 5% level even when controlling for (log of) firms' sales and for firm-year fixed effects, respectively.

Interestingly, the results are the opposite for the group of white collar workers. White collar female workers see an increase in wages of 0.011% compared to their male colleagues, as their employers rise their export share by one percentage point. As in the case for blue collar workers, these results are robust to the inclusion of additional controls for firm productivity and of firm-year fixed effects. There is a slightly negative effect of export on the wages of white collar male workers', which is however only significant when controlling for firms' sales (column (8)).

Furthermore, an increase in (total) firms' sales has a negative effect for female workers in blue collar occupations which is only significant in specification (3.2) when firm-year fixed effects are not considered (column (2)), while it seems to benefit both female and male workers in white collar occupations.

As anticipated, approximating the export intensity of firms by the firms' export share does not give us a direct measure of the elasticity of export on wages and gender wage gap, but more importantly, the estimated coefficients are not immediately comparable with the effects of an expansion in firms' sales in domestic markets. For this reason, we use an alternative measure of firms' export intensity - (the log of) the total sales form export- to be able to compare it with the effect of an increase in (the log) of domestic sales. Since, this only allows us to focus on the sample of exporting firms, we also report the results focusing on this type of firms only. In this case, the effect becomes slightly stronger, indicating that one percentage point increase in the firms' export share positively affects the gender wage gap among blue collar workers by 0.017% (column (4)) and reduces it among white collars by 0.015% (column (9)). The elasticity estimation shows that a 10% increase in firms' export sales increases gender wage gap by 0.028% among blue collar (column (5)), and decreases gender wage gap by 0.047% among white collar (column (10)). On the other hand, the effect of domestic sale is positive among blue collar, in the sense that it reduces the gender wage gap, and non significant among white collar.

The estimation results of the models that include a triple interaction term between the female dummy, the export variable and the white collar dummy, described in specification (3.4) are reported in Table 3.5. They largely confirm the evidence from the baseline estimation on the different groups of white and blue collar workers described above.

First, in column (1) we report the results of the estimation of model (3.4) using the variable export share as proxy for the firms' export activity. The coefficient on the triple interaction term, $\hat{\epsilon_4}$, reveals the presence of a strongly significant differentiated impact of export on gender wage gap for white collar relative to blue collar workers. Specifically, a one percentage point rise in export share induces a divergence in the gender wage gap between white and blue collar workers by 0.027%. This seems to be due to both a rise of the gender wage differential for blue collar workers and a reduction for white collar workers. The coefficient that informs about the female wage premium for blue collars ($\hat{\epsilon_2}$) is in fact negative and statistically significant at the 5% level, indicating that a one percentage point increase in the firms' export share increases the gender wage gap among blue collar workers by 0.0145%. Additionally, the estimation results show that this effect can be attributed mostly to a drop in wages of blue collar female workers, given that wages on theirs male colleagues are not affected by export (the coefficient $\hat{\epsilon_1}$ is close to 0 and not significant). Conversely, a one percentage point rise in firms' export share seem to significantly reduce the gender wage gap for white collar workers by 0.0128%.[15] In this case, we can say that both white collar men and

[15]The total effect of export on gender wage gap for white collars is given by the sum of coefficients $\hat{\epsilon_2} = 0.0273$ and $\hat{\epsilon_4} = 0.0145$. They are both statistically significant at 5% and 1% level respectively.

women benefit from trade, but the positive effect on women is stronger than for men. In particular white collar women wages increase by 0.0245% following a unit increase in the export share, while wages of white collar men only by 0.0117%.[16]

These results are further confirmed if we modify equation (3.4) to control for observable firms' characteristics (column (2)), firm-year fixed effects (column (3)) and when the sample is shrunk to only consider exporters (column (4)). The effect of export on gender wage gap is significantly different for white and blue collars, being positive and statistically significant for the former group and negative and statistically significant for the latter. Additionally, an increase in total sales seem to have no significant effect of the gender wage gap for blue collar workers, and a slightly negative effect on the gender wage gap for white collar workers (see column (2) and (3)).[17]

The results for the estimation of the specification that uses the alternative measure of firms' export intensity - (the log of) the total sales form export- and (the log) of domestic sales are reported in column (5) of Table 3.5. They confirm that, even when we net out the unobserved heterogeneity at the match and firm-time level, what really matters for the gender wage gap is firms' export activity rather than domestic sales. Specifically, we obtain that an increase in firms' sales abroad reduces gender wage gap for white collar workers, while a rise in domestic sales seem to be irrelevant for it. A 10% increase in export sales contributes to close the gender wage gap among white collar employees by roughly 0.05%, while no significant effects are found for blue collar workers.[18] The coefficient that informs us about it, $\hat{\epsilon_2}$, is in fact non statistically significant. Furthermore, a rise in firms' domestic sales has no significant effect on the gender wage gap neither for blue collar or white collar female workers but, interestingly, it reduces the skill premium for white collar male workers.

In light of the evidence shown in this section, we can conclude that firms' export activity benefits white collar female workers and harms their blue collar colleagues, both in absolute terms and relative to their male coworkers. This seems a strong stylized fact for our observational sample which poses interesting challenges for its interpretation. In the next section we take on these challenges

[16]The effect of export on white collar women wages is computed from the convolution of parameters $\hat{\epsilon_1} + \hat{\epsilon_2} + \hat{\epsilon_3} + \hat{\epsilon_4} = 0.0273 + 0.0117 - 0.0145 - 0.0006$. The effect on male white collar wages is given by $\hat{\epsilon_1} + \hat{\epsilon_3} = 0.0117 - 0.0006$

[17]Similarly to interpretation of the coefficients for the export variable, the effect of total sales on gender wage gap of white collar female workers is given by the sum of the coefficient of the triple interaction $(Fem_i * wc_i * ln(S_{jt}) = 0.0077$ and the double interaction $Female * ln(S_{jt}) = 0.004$ (see column (2), results are similar when firm-year fixed effects are taken into account (column (3))).

[18]The total effect on gender wage gap on white collar employees is given by $\hat{\epsilon_2} + \hat{\epsilon_4} = 0.0082 - 0.003$.

by investigating some of the possible mechanisms that may drive these empirical results.

3.4 Export and the Gender Wage Gap: Exploring the Mechanisms

So far, we have investigated the effects of firms' export activity on workers' wages. For the purpose of our identification strategy, we have mostly focused on changes in wages of workers staying within the firm as it intensifies its exports. We have found no significant effect on the gender wage gap in general, which masks a strong and positive effect on white collar female workers' wages and a negative one on blue collar female workers. Moreover, we have shown an increase in domestic sales to have a significantly weaker effect than an expansion in export. In this section we try to understand the channels that may be driving these results.

The fact that the gender wage gap reacts more to export than domestic sales suggests that selling to foreign markets may require the firm to change the intensity in the use of certain skills in a way that makes women relatively more demanded in non-production tasks. This is aligned with the existing evidence that women tend to have a comparative advantage in performing white collar tasks, especially those intensive in interpersonal relations and in the use of computers, while they have a disadvantage in blue collar, "brawn"-intensive occupations (see Spitz-Oener, 2006; Black and Spitz-Oener, 2010; Borghans, Weel and Weinberg, 2014, Petrongolo and Ngai, 2014; Cortes et al., 2018). If export requires a more intensive use of "male" skills in production (e.g., because it changes the production line in a way that calls for more "brawn"), and of "female" skills in non-production tasks (e.g., because it takes more ability in interpersonal relations to deal with foreign customers), an expansion in foreign activities will increase (decrease) the demand for females in white-collar (blue-collar) occupations. We assess this mechanism, based on gender-specific comparative advantage following three steps.

First, we check whether labour demand responds to changes in export consistently with the proposed mechanism. Unfortunately, given that we do not observe the number of hours worked in the LIAB dataset, we can only focus on the extensive margin of labour demand, leaving the effect on the intensive margin to be the object of investigation in future research.

Second, given that our identification strategy focuses on changes in relative wages of workers that stay within the firm as it exports more, we look at the effect of export on the (relative) probability of promotions especially of female white collar workers. As it has been recently shown by Bronson and Thoursie (2017), differences in promotion rates are an important determinant of the gender wage gap, explaining most of the lifecycle wage differences between women and men. Exploring the effect of export on promotion probabilities seems therefore a useful exercise to shed some light on what drives the drop in gender wage gap among white collar workers. Following Black and Brainerd (2004), we may argue that as the firm intensifies its export activity and faces more competition, it reduces its discriminatory practices by promoting women more. Or, similarly, it may be that white collar female workers become particularly valuable to the firm as it exports more, so that the firm promotes them in order to retain them.

To investigate further whether women performing specific tasks are more valuable and more paid as the firm exports more, we also split the samples of blue and white collar workers in groups of occupations classified according to the intensity of tasks performed on the job. Specifically, we consider five occupational sub-categories: manual routine, manual non-routine, cognitive routine, analytic non-routine, and interactive non-routine. On this sub-samples we estimate the same regressions presented in Section 3.3.1.

3.4.1 Export and Firms' Labour Demand

In this section we explore the effects of export on firms' labour demand. Specifically, since we observe a rise (drop) in wages of white (blue) collar female workers relative to their male colleagues in the same occupation, we want to test whether this effect is accompanied by an increase (decrease) in the firm relative demand for this group of workers. Unfortunately, given that we do not observe hours worked, we can only look at the effects of export of firms' labour demand at the extensive margin. Since in the wage analysis we only focused of full time workers, we do the same here and only consider employed the workers that are employed full time.

Specifically, we estimate the following linear model at the firm-year level:

$$Y_{jt} = \gamma_1 \ln Exp_{jt} + \mathbf{F}'_{jt}\beta_1 + \eta_j + \varepsilon_{jt} \tag{3.5}$$

where the dependent variable Y_{jt} represents, respectively, (1) the total share of white collar workers, (2) the total share of women among white collars and, lastly, (3) the total share of women among blue collars.

One caveat of this specification is that it only allows to look at the correlation between firms' export and the total share of workers, without distinguishing between new-comers and stayers. Thus, to fully understand if and on which component of the workforce the firm is implementing the changes, we also estimate model (3.5) using only the sub-sample of newly hired workers. These are defined as workers that are employed in firm j at time t but were not employed in firm j

at time $t-1$, $t-2$ and $t-3$.

We use the (*log* of) export as proxy for firm's export activity and we always control for the the (*log* of) domestic sales as proxy for firm's productivity.[19] As a robustness check, we also estimate the same relationship using the (*log* of) export and domestic sales at time $t-1$, since it is plausible that demand adjustments as a response to changes in export may take one period to implement.

Unfortunately, in this specification we can only control for firms' time invariant unobserved heterogeneity, since including firm-year fixed effects would not allow us to estimate the impact of export on the changes in the shares of workers within the firm. We are aware that this prevents us from drawing conclusions on the causal effect of sales from export on changes in firms' labour demand. However, we believe that studying correlations between firms' export activity and workforce composition can be informative for our analysis.

The results of the models' estimations exploiting within-firm variation are reported in Table 3.6. In column (1) we show firm's export and domestic sales to be non-significantly correlated with the share of white collar workers. Column (2), however, suggests that as the firm exports more, it employs more female white collars relative to male. This result holds and becomes even stronger if we keep the share of female workers from the previous period constant. This variable is used as a control for firm-specific factors, like hiring preferences, and it strongly predicts gender workforce composition among white collars, as shown in column (3). Finally, when we turn to the share of female blue collars in columns (4) and (5), we find no significant correlation with firms' export and a weak positive association with domestic sales, which disappears as we control for the share of female workers in the firm.

Results from the estimation of model (3.5) for newly hired workers are reported in Table 3.7.[20] The coefficients for the log of export are non-significanlty different from zero across all specifications for the number of new hires and the share of female workers in newly hired white and blue collars. We find similar results for both the total demand and hiring patterns even when we use the lagged value of export and domestic sales as explanatory variables (see Table 3.8 and 3.9).

In conclusion, more export activity within the firm is associated to a slightly higher share of female white collar workers and no significant changes in the share of female blue collar workers. No significant results are found when we check if the

[19]We find similar results even when we use the share of export on total sales as a measure of firms' export activity.

[20]When reading these results we have to keep in mind that in the whole dataset the share of newly hired workers relative to the whole workforce is equal to 3%, showing that most of the workers where already employed in the firm as the survey started.

adjustment is happening at the hiring margin. Thus, the reduction in gender wage gap for white collar female workers seems not to be driven by a significant increase in the firm demand at the extensive margin for this group of workers. However, if no additional white collar women (relative to men) are hired by the firm as it exports more, the ones with positive tenure within the firm could also be asked to increase their working hours to meet the firm' rise in demand, contributing to reduce the gender wage gap. Unfortunately, we cannot test whether the channel of labour demand at the intensive margin is relevant, given that our data do not have information of working hours.

3.4.2 Export and Promotions

After showing export to only slightly increase the relative demand for women in white collar occupations, we now investigate whether white (blue) collar female workers employed within the firm become relatively more (less) valuable as the firm exports more. We do so by looking at the effects of export on the relative probability of promotion of female workers for white and blue collar workers. We use the same identification strategy of Section 3.3.2 and focus on workers that stay within the firm as it expands its export activity. In this way we control for possible sources of bias due to match-specific unobserved heterogeneity. Unobserved match heterogeneity could bias the results because if the firm employs better workers as it exports more it can also be inclined to promote them more.

To define the probability of promotion we follow Bronson and Thoursie (2017) and record a promotion as a given discrete percentage change in an individual's wage compared to the rest of the co-workers in the same broad occupation category (white collar versus blue collar). In practice, we first compute the average yearly wage growth rate of the two groups of white and blue collar workers in the same firm and year. Then, we consider a worker to be promoted if he or she experiences a change in wages that is 10% higher compared to the rest of the workers within his or her occupation category.[21]

Promotions are very few in the dataset: among people that stay within the firm for at least two periods, we only observe on average 5.63% of promotions.[22] This result is in line with the literature, for example for Swedish data Bronson

[21] As a robustness check, we also slightly modify the definition of promotion by only considering a worker to be promoted if he or she experiences a change in wages that is 15% higher compared to the rest of the workers within his or her occupation category.

[22] The percentage of promotions in the dataset is equal to 2.40% when we use the second definition of promotions, in which we only consider a worker to be promoted if he or she experiences a change in wages that is 15% higher compared to the rest of the workers within his or her occupation category.

and Thoursie (2017) find that promotions only occur two or three times maximum in a worker's life.

Specifically, in line with Section 3.3.1, we estimate the following linear probability model:

$$\begin{aligned}\Pr(promotion)_{ijst} =&\zeta_1 Exp_{jt} + \zeta_2 fem_i * Exp_{jt} + \zeta_3 wc_i * Exp_{jt} + \\ &\zeta_4 fem_i * wc_i * Exp_{jt} + \mathbf{C}'_{it}\upsilon_1 + \mathbf{F}'_{jt}\upsilon_2 + \eta_{st} + \eta_{ij} + \varepsilon_{ijst}\end{aligned} \tag{3.6}$$

where, $\Pr(promotion)_{ijst}$ represents the probability of individual i in firm j in sector s of receiving an increase in the salary at time t relative to time $t-1$ that is higher than 10% the average increase in salary of his/hers colleagues. Here, we directly use the (log of) sales from export to proxy the export variable and we control for the (log of) domestic sales as a proxy for firm productivity, to obtain a direct measure of the elasticities of promotion to these two variables. We estimate the model also controlling for firm-year fixed effects in order to take into account possible sources of bias that may affect both export decision and probability of promotion. The interpretation of the parameters follows the explanation in Section 3.3.2. We are particularly interested in the estimation of parameter ζ_4, which informs us about the extent of the gender gap in the probability of being promoted among white collar relative to blue collar workers.

The estimation results of model (3.6) are reported in Table 3.10. In column (1) we show the baseline results, and in column (2) the outcome of the estimation that includes firm-year fixed effects. The baseline results show a negative and significant effect of export on the probability of promotion of blue collar male workers (coefficient $\hat{\zeta_1}$) and a positive and significant effect of export on the probability of promotion of white collar male workers (coefficient $\hat{\zeta_3}$). We find that the coefficient for the triple interaction term, $\hat{\zeta_4}$, is positive but not statistically significant signalling no differential impact of export on the probability of promotion for white collar female workers relative to their male white collar colleagues. Interestingly, an increase in domestic sales seems to have similar effects of a rise in export, fostering career progressions of white collar male workers and reducing the promotion probability of blue collar male workers. It also seems that white collar female workers see their probability of being promoted reduced as the firm increases domestic sales.

However, once we subsume firm's export and domestic sales with firm-year fixed effects, results are different: the estimates in column (2) shows a positive and significant coefficient for the triple interaction term, $\hat{\zeta_4}$, equal to 0.0053, which indicates that white collar women face a higher probability of being promoted relative to men as the firm intensifies its exports.[23]

Interestingly, the effect of an expansion of domestic sales has opposite sign, indicating that white collar men mostly benefit from this in terms of promotions. No significant effects of both export and domestic sales are found for men and blue collar workers.

In conclusion, we can say that the reduction in gender wage gap for white collar workers is accompanied by a slightly higher probability of promotion for white collar female workers, as firms intensify their export activity. This may indicate that, as firms export more, their matches with female white collar workers become increasingly valuable. This would be justified by the presence of a comparative advantage of this group of workers in tasks which the firm values more as it exports more.

3.4.3 Export, Gender Wage Gap and Occupational Task Content

Up to now we have documented a reduction and a rise in the gender wage gap among white and blue collar workers, respectively, associated with the increase of firms' export intensity. We have also shown that this is accompanied by a positive correlation between firms' export and share of female employees among white collar workers (with no significant changes in hirings) and by a slight increase in the relative female-male promotion probability among white collars compared to blue collars.

The combination of these empirical facts seems to indicate that white collar women employed in firms that intensify their export activity perform jobs particularly valuable to this end. In support to this, previous research has documented that international firms value more non-routine, interactive jobs compared to routine ones (Becker, Ekholm, and Muendler, 2013). In parallel, a growing body of literature documents that women have a comparative advantage in non-routine tasks requiring interpersonal skills, whose demand has increased in the past decades, contributing to the reduction in the gender wage gap (Spitz-Oener, 2006; Black and Spitz-Oener, 2010; Borghans, Weel, and Weinberg, 2014; Olivetti and Petrongolo, 2016; Cortes, Jaimovich, and Siu, 2018).

The availability of detailed data on the content of the activities performed on the job by workers in Germany is a powerful resource to empirically test the validity of this channel. Specifically, we classify occupations according to their

[23] Results do not change significantly when we increase from 10% to 15% the threshold of relative wage increase in the definition of promotion (see Table 3.11).

"task content", that is the detailed set of activities performed on the job, using the information provided in the "Survey on qualification and working conditions" (BiBB/IAB and BIBB/BAuA- 91/92, 98/99, 2006), and estimate the effect of firms' exports on the gender wage gap for each occupational sub-category. In the econometric analysis, we use the same estimation framework described in Section 3.3.1 in models (3.1), (3.2), (3.3).

The "Survey on qualification and working conditions" consists of a repeated cross section of a random sample of workers covering 0.1 percent of the German labour force. It contains detailed information on workers' attributes (age, gender, education), earnings and occupation, as well as information on the workplace characteristics. In particular, it provides detailed data on the set of activities performed in each job, that allows us to classify 15 longitudinally consistent tasks, following the methodology given in Becker and Muendler (2014). Based on the definition of tasks, we follow Spitz-Oener (2006) and group occupations in five sub-categories based on the activity performed more often on the job. The five sub-categories are: 1) Manual routine, 2) Manual non-routine, 3) Cognitive non-routine, 4) Analytic non-routine, 5) Interactive non-routine. A detailed description of the definition of tasks and their mapping into occupation categories is provided in Appendix 3.B. After we assign one category for each occupation based on its task content, we link the information to the LIAB dataset using the occupational code KldB2010 with three digit level of detail. This allows us to obtain a unique matched employer-employee dataset with detailed information on the activities performed by workers on the job.

We show the breakdown of occupation categories by task content for white collar and blue collar workers in Table 3.12. In our dataset, 70% of white collar occupations are categorized as interactive non-routine, followed by 21% categorised as analytic non-routine, and less than 10% classified as manual.[24] Among blue collar occupations, 64% are classified as manual routine, 21% as interactive non-routine and 8% as manual non-routine.[25]

We perform our estimation on all sub-categories of occupations for white and blue collar workers, but we only report the results for the most representative ones for both groups. That is, we report the estimation results of models (3.1), (3.2), (3.3) for interactive non-routine and analytic non-routine occupations for white collar workers in Table 3.13, and for manual routine, interactive non-routine

[24]Examples of white collar manual routine jobs are: postal deliverers, railway engine drivers, office auxiliary workers and of white collar manual non-routine jobs: nurses, social workers, care workers.

[25]Some relevant examples of blue collar interactive non-routine jobs are: waiters, stewards, domestic and non-domestic servants, Watchmen, custodians, cooks.

and manual non-routine occupations for blue collar workers in Table 3.14. More specifically, for each sub-group of occupations, in the first column of the results tables, we report the estimates of baseline model (3.1), in which use the firms' export share on total sales to proxy for firms' export activity, and we control for match fixed effects only (in addition to federal state, sector-year fixed effects). In the second column, we report the estimates of model (3.2), in which we add controls for firm productivity proxied by the firm's total sales. In the third column, we show the results of the estimation of model (3.3), in which we add to the previous specification controls for firm-year fixed effects to absorb shocks at the firm-year level that could bias the results. The fourth column of each sub-category shows the estimated gender wage gap elasticity to export and domestic sales, computed on the restricted sample of exporting firms.

The estimation results reported in Table 3.13 show no significant relation between firms' export activity and the gender wage gap for white collar workers employed in analytic non-routine occupations. In fact, the estimates in all model specifications are not statistically significant. On the contrary, white collar female workers mostly performing interactive tasks, seem to benefit from firms' export activity significantly. More specifically, column (5) of Table 3.13, in which we report the results of the estimation of the baseline model, shows that a one percentage point increase in export share is associated to a 0.0071% increase in the relative wage of female employees, statistically significant at the 5% level. The effect on the (log) wages of male employees is also positive, but smaller in size and not statistically significant, indicating that the reduction in the gender wage gap is mostly attributable to a rise in wages of tenured female employees. The correlation between export share and relative wages of female employees working in this group of occupations stays positive and significant even when we control for the (log of) the firms' total sales and doesn't vary significantly in size (column (6)). In this case, a 1% increase in export share reduces the gender wage gap by 0.0067%. Additionally, an increase in firms' total sales has a positive effect both on the relative wage of female employees and on the wages of male employees. Adding firm-year fixed effects (column (7)) doesn't make the coefficient that captures the relation between export share and the gender wage gap vary significantly in size, but in this case it is no longer statistically significant. Interestingly, the relative female-male wage elasticity to export sales is positive and significant at the 1% level for this group of workers, indicating that a 10% increase in export sales contributes to close the gender wage gap for this group workers by roughly 0.03%, while the gender wage gap seem to not respond to variation in domestic sales (column (8)).

The results for the sub-groups of blue collar workers in Table 3.14 show that women employed in manual routine occupations are significantly disadvantaged by the firm's export activity. Specifically, a one percentage point increase in export share is associated with a 0.02% reduction in the relative wage of female employees, statistically significant at the 1% level (column (1)), while the (log) wage of male workers in this category seems not to be significantly affected by export. The results are confirmed even controlling for firms' total sales (column (2)). Additionally, a rise in firms' total sales is associated with a statistically significant increase in the wage of male employees and with a statistically significant decrease in the relative wage of female employees. Adding firm-year fixed effects (column (3)) partly absorbs the effect of export on gender wage gap, thereby reducing the magnitude of the coefficient representing the relation between the two variables, but without affecting the sign nor the statistical significance. Specifically, the estimates indicate that a one percentage point increase in export share is associated to a 0.01% reduction in the relative wage of female employees, statistically significant at the 1% level. Finally, the estimated elasticity of female employees relative wage to export sales and domestic sales are, respectively, negative and positive, but not statistically significant (column (4)). The results for the sub-group of blue collar manual non-routine workers are in line with the ones on the manual routine occupations, showing a negative effect of export on the relative wages of female blue collar employees, but they are not statistically significant for all the estimated specifications. The only exception is the one reported in column (6), in which we estimate the model controlling for firms' total sales. In particular, it shows a strong and statistically significant negative correlation between export and relative wage of female workers. Firms' exports seem not to have any significant effect on wages of blue collar workers performing interactive non-routine jobs. However, in contrast with the results for the other occupational sub-categories for blue collar workers, in this case a rise in domestic sales seems to significantly contribute to the closure of the gender wage gap.

In light of these results, we can conclude that the total positive effect of an increase in firms' exports on the relative wage of white collar female workers, discussed in Section 3.3 and reported in Tables 3.4 and 3.5, is likely to be driven by increases in wages of female workers employed in occupations in which interactive non-routine tasks are most intensively performed. Additionally, it seems that the widening of the gender wage gap in response to firms' exports expansion among blue collar workers is mostly driven by manual routine occupations. However, we have seen that the estimated gender wage gap elasticities to export are not significant for blue collar workers in general and, specifically, for the sub-group of manual routine workers.

These results seem to justify the validity of the comparative advantage channel in explaining the correlations between firms' export expansion and reduction in gender wage gap for (tenured) white collar workers. As the firm expands its exports, it values more highly qualified workers performing non routine interpersonal jobs, for which women have a comparative advantage. This induces the firm to increase their wages, as for example to pay them for a production bonus or simply in order to retain them, thereby contributing to the closure of the gender wage gap.

3.5 Robustness Checks

In this section we perform some checks to make sure our results are robust to changes to the models' specification.

Our main concern is given by censoring in the wage variable. As explained in Section 3.2, the information on wages provided in the LIAB dataset is censored up to a contribution limit. Specifically, 13% of wages are censored in the whole dataset. This issue mostly affects white collar workers, among which 33% of observations results to be censored, while it only affects 4% of observations in the group of blue collar workers. Additionally, among white collars, the share of censored wages for male and female workers are respectively equal to 46.45% and 8.76%.

Therefore, if exports affected wages of men above the contribution limits, we would not be able to see its true effect, and our results on the closing gender wage gap among white collar workers may be biased.

The approaches in the literature to deal with this issue are essentially two, one is to drop censored observations (see Baumgarten, Geishecker, and Görg, 2013), and the other one is to impute a wage using a Tobit model for censored data (see Schank, Schnabel, and Wagner, 2007). For now, we depart from these two approaches and deal with this problem differently.[26] Specifically, we check whether our estimation of the impact of export on wages for white collar workers is mostly captured by the censored observations. In practice, we estimate the following

[26]Given that our analysis focuses on the differential effects of trade on white and blue collar workers, and that a high share of wages of white collar workers is censored, we prefer not to drop these observations in order to not lose relevant information and estimation power. Additionally, we do not perform wage imputation because we would have to take into account in the procedure firms' export, given that it represents the focus of the analysis. Schank , Schnabel and Wagner (2007) have a similar problem and imputes wages of white collar workers by draws of a random variable using a truncated distribution, by also considering firm level fixed effects in the imputation procedure. He finds a slightly higher effect of export on wages when using imputed wages.

linear model on the sub-sample of white collar workers:

$$\begin{aligned}\ln w_{ijst} =&\zeta_1 Exp_{jt} + \zeta_2 fem_i + \zeta_3(fem_i * Exp_{jt}) + \zeta_4 cens_{i,t-1}+\\ &\zeta_5(fem_i * cens_{i,t-1}) + \zeta_6(cens_{i,t-1} * Exp_{jt})+\\ &\zeta_7(fem_i * Exp_{jt} * cens_{i,t-1}) + \mathbf{C}'_{it}\chi_1 + \mathbf{F}'_{jt}\chi_2 + \eta_{st} + \eta_{ij} + \varepsilon_{ijst}\end{aligned} \tag{3.7}$$

where, $cens_{i,t-1}$ is a dummy variable indicating whether the wage observation was censored at time $(t-1)$.

The model mimics specification (3.4), and the source of identification follows the main estimation strategy, which exploits variation of wages for workers staying within the same firm as it varies its exports throughout time. Similarly to what we do in Section 3.3.2, we estimate equation (3.7) first approximating the firm's export activity with the export share and then with the *log* of export. We also estimate the model including firm-year fixed effects.

The results of the estimation are reported in Table 3.15. In column (1) we show the estimates of the baseline estimation, in column (2) the estimates of the model specification with firm-year fixed effects, in column (3) we report the results only for the sample of exporting firms and in column (4) we report the estimates the relative wage elasticity to export and domestic sales obtained by using the *log* of export and of domestic sales.

In all specifications, we find a positive and significant coefficient $\hat{\zeta}_3$, which implies that export is associated with a reduction of the gender wage gap for workers that are not affected by wage censoring. Additionally, we find a small and positive effect of export on wages for women affected by censoring and an slightly negative effect on men in the same category.[27]

The fact that we find an effect of export on gender wage gap for workers not affected by censoring that is in line with the main results, provide some confidence for the validity of our estimations, at least from a qualitative point of view.

To further validate our results we perform some additional robustness checks. In Table 3.16 we report the results of the estimation of model (3.4) for the differential impact of export on blue collar and white collar workers using the (one period) lagged value of export instead of the current value. We may in fact think that wages adjustment relative to changes in firms' export are not immediate and could take some time to implement, so that the current value export is a biased measure which is picking up some other factor. The results confirm the predictions of the main specification showing a drop in the gender wage gap for white collar

[27]The effect of export on censored wages of female workers is given by the sum of coefficients $\hat{\zeta}_1$, $\hat{\zeta}_3$, $\hat{\zeta}_6$ and $\hat{\zeta}_7$; while the effect on censored wages for male workers if given by $\hat{\zeta}_1 + \hat{\zeta}_6$.

workers. However, the results for blue collar workers are not significant.

We also run the same model on the sub-sample of high-tenure workers (with more than three years of continuous employment within the same firm). The results are reported in Table 3.17, and confirm that export has a negative effect on the gender wage gap for white collar workers, independently of whether these are recent hires.

Finally, to gauge the importance of adopting our idenfication strategy, based on within firm-worker variation, and for better comparability with previous works, in Appendix C, we estimate the main specifications of Tables 3 and 4 exploiting only within-sector and within-firm variation. The results show export to be associated to a reduction in the gender wage gap for both blue and white collar workers. This, compared to the evidence in Section 3 indicate the key importance of the sorting between firms and workers in driving the results.

3.6 Conclusions

International trade has long been considered as one of the main causes of the increase in income inequality, by favouring some workers and penalizing others. At the same time, the investigation of the forces driving the gender wage gap - declining in the recent years, but still existent - has attracted the attention of academic economists and policy makers. However, the relationship between these two important trends has received little attention.

We contribute to filling this gap in the literature by investigating the role of firms' export activity on the gender wage gap, using matched employer-employee data on Germany for the 1993-2007 period. The structure of the dataset allows us to observe the changes throughout time in export sales of the single firm and the evolution of wages of all the workers employed by that specific firm. We exploit this feature of the data to estimate what we believe is the causal relationship between exports and the gender wage gap. Specifically, we focus on the same pair of female-male workers employed in the firm and look at the changes in their relative wages as the firm expands its export activity. This specification is likely to reveal the causal effect of export on the gender wage gap because it takes into account the possible sources of bias related to individual and firm characteristics, sorting and reverse causality issues.

Our first baseline estimates reveal no effect of export on the gender wage gap on average. However, when we split the sample by workers' occupation, we find that an increase in export reduces the gender wage gap among white collar workers and increases it by a similar amount among blue collar workers.

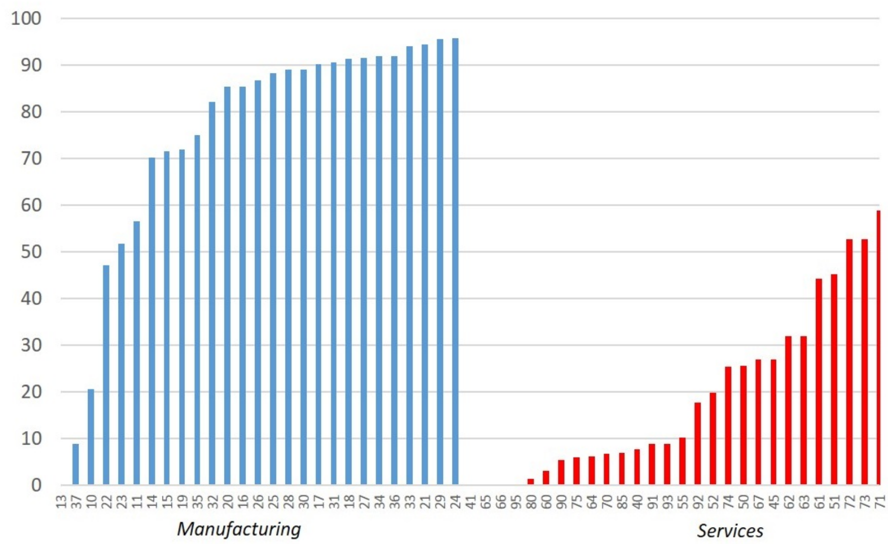
When probing deeper into the mechanism behind this result, we find evidence supporting the hypothesis that export reinforces female comparative advantage in tasks considered more important by international firms, such as the non-routine interactive ones. In particular, we show that the results on the closing gender wage gap for white collar workers are mostly driven by the sub-group of workers that perform more interactive non-routine jobs.

A limitation of our data is the lack of information on the number of hours worked by each employee. Availability of this variable would allow us, in future work, to estimate the effect of export on the intensive margin of the demand for labour at the worker-firm level and hence to further assess our proposed mechanism through gender comparative advantage.

The evidence in this paper provides some important insights. First, it highlights the role of trade as an opportunity for the reduction of the gender wage gap among non-production workers, but also as a threat especially for women in occupations for which they have a comparative disadvantage. Besides underscoring a so far overlooked determinant of gender disparities in earnings, this is relevant for policy makers, since it suggest for instance how to structure re-training programmes in such a way that globalisation helps to reduce the wage gender gap for more women. Second, it contributes to the understanding of the sources of comparative advantage in trade models. An interesting implication of our resuts is that variation in female labour force participation may help explaining the differences in export performance across countries (see Bonfiglioli, Crinò, and Gancia, 2019) and over time. Linking our micro evidence to aggregate outcomes seems therefore an interesting avenue for future research.

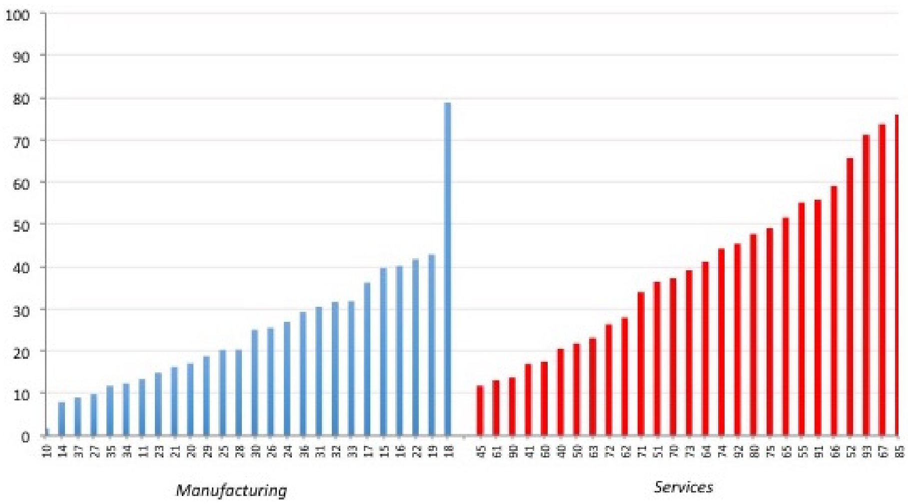
3.7 Figures

Figure 3.1 – Average Percentage of Exporting Firms by Sector in West Germany, 1993-2007



Notes: All numbers refer to average share of exporting firms operating in West-Germany during the years 1993-2007 by sector of activity classified according to the NACE Rev.2 system. The x-axis represents the sector of activity.
The data source is the LIAB dataset for years 1993-2007.

Figure 3.2 – Average Percentage of Female Workers by Sector in West Germany, 1993-2007



Notes: All numbers refer to average share of female workers in West-Germany during the years 1993-2007 by sector of activity classified according to the NACE Rev.2 system. The x-axis represents the sector of activity.
The data source is the LIAB dataset for years 1993-2007.

3.8 Tables

Table 3.1 – Firm Export Activity in West Germany, 1993-2007

	IAB Establishment panel	LIAB MEE data
Share of exporting plants	22%	33%
Share of exports on total sales	7%	31%
Employment share of exporting plants		68%
Share of firms switching export status		5%
Average number of switches of export status per firm		1.9

Notes: All numbers refer to averages of the indicated variables for the sample of establishments operating in West-Germany during the years 1993-2007. The data sources are IAB Establishment panel and LIAB dataset.

Table 3.2 – Exporters vs Non-Exporters Characteristics by Gender

	Non Exporting Firms			**Exporting Firms**		
	All	Male	Female	All	Male	Female
Ln(Firm size)	6.38			7.52		
Ln(Total sales)	18.18			19.64		
Female share or labour force	0.25			0.18		
Log daily wage	4.47	4.53	4.28	4.58	4.62	4.39
Experience (years)	15.99	16.56	14.35	16.19	16.50	14.80
Age	38.43	38.95	36.92	38.68	39.00	37.26
Education						
1. low skill	0.19	0.18	0.21	0.19	0.17	0.32
2. medium skill	0.71	0.71	0.71	0.68	0.69	0.60
3. high skill	0.10	0.10	0.08	0.13	0.14	0.08
Occupation						
1. White collar	0.41	0.31	0.72	0.28	0.23	0.46
2. Blue collar	0.59	0.72	0.28	0.72	0.77	0.54

Notes: All numbers refer to average values of the indicated variables for the sample of establishments operating in West-Germany during the years 1993-2007 and are computed on the linked dataset (LIAB). Firm size represents the average number of full time employees in the firm. The establishments total sales and daily wages are expressed in real values, converted in (Euro) 2000 prices using the German CPI index.

Table 3.3 – GWG and Exports: All Sample

	(1)	(2)	(3)	(4)
Export share	0.0028	-0.0007	-0.0005	
	(0.004)	0.005	(0.005)	
Female* Export share	0.0018	0.0007	0.0001	0.0049
	(0.005)	0.006	(0.006)	(0.005)
Ln(total sales)		0.0090***	0.0090***	
		0.002	(0.002)	
Female*ln(total sales)			-0.0015	0.0004
			(0.002)	(0.001)
Experience/10	0.2513***	0.2452***	0.2467***	0.3647***
	(0.02)	0.02	(0.021)	(0.023)
Experience sq./100	-0.0442***	-0.0444***	-0.0444***	-0.0452***
	(0.001)	0.001	(0.001)	(0.001)
White Collar	0.0268***	0.0279***	0.0279***	0.0268***
	(0.002)	0.002	(0.002)	(0.002)
Ln(firm size)	0.0297***	0.0231***	0.0230***	
	(0.004)	0.004	(0.004)	
Federal State FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	No
Match FE	Yes	Yes	Yes	Yes
Firm-Year FE	No	No	No	Yes
Observations	9,283,280	8,024,723	8,025,555	8,024,165
R-sq.	0.947	0.947	0.946	0.951

Notes: The dependent variable is log wages in real values. Note that including firm-year fixed effects in the estimation makes sector-year fixed effects redundant, since firms do not change sector of activity in the estimation sample. The data source is the LIAB dataset for years 1993-2007.
*/**/*** denote significance at the 10/5/1% level respectively. Standard errors are in brackets and are clustered at firm level.

Table 3.4 – GWG and Exports: Blue Collar vs White Collar

	Blue Collar					White Collar				
					Elasticities					Elasticities
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Exp_{jt}	0.00516	0.00268				-0.0019	-0.0056*			
	(0.005)	(0.007)				(0.003)	(0.003)			
Female * Exp_{jt}	-0.0161**	-0.0211***	-0.0123**	-0.0171**	-0.0028***	0.0115***	0.0137***	0.0117**	0.0152**	0.0047***
	(0.007)	(0.008)	(0.006)	(0.007)	(0.001)	(0.004)	(0.005)	(0.005)	(0.006)	(0.001)
$Ln(S_{jt})$		0.0102***					0.0044***			
		(0.002)					(0.001)			
Female * $Ln(S_{jt})$		-0.0038*	-0.0018	-0.0022	0.0020**		0.0040**	0.0040**	0.0079***	0.0003
		(0.002)	(0.002)	(0.002)	(0.001)		(0.002)	(0.002)	(0.002)	(0.002)
Experience/10	0.1989***	0.1894***	0.3057***	0.2959***	0.2948***	0.3997***	0.4082***	0.5558***	0.5104***	0.5084***
	(0.019)	(0.02)	(0.019)	(0.022)	(0.022)	(0.029)	(0.032)	(0.047)	(0.054)	(0.054)
Experience sq./100	-0.0375***	-0.0377***	-0.0392***	-0.0382***	-0.0382***	-0.0607***	-0.0612***	-0.0611***	-0.0631***	-0.0631***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
Ln(firm size)	0.0421***	0.0334***				0.0142***	0.0114***			
	(0.005)	(0.004)				(0.002)	(0.002)			
Federal State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Match FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Observations	6,429,934	5,580,870	5,578,197	4,274,680	4,264,457	2,821,512	2,417,122	2,412,202	1,547,613	1,541,925
R-sq.	0.936	0.935	0.943	0.939	0.939	0.954	0.953	0.956	0.948	0.948
Sample	Blue Collar, All firms	Blue Collar, All firms	Blue Collar, All firms	Blue Collar, Only Exporters	Blue Collar, Only Exporters	White Collar, All firms	White Collar, All firms	White Collar, All firms	White Collar, Only Exporters	White Collar, Only Exporters

Notes: The dependent variable is log wages in real values. The results reported in columns (1)-(2)-(3)-(4)-(5) refer to blue collar workers and those in columns (6)-(7)-(8)-(9)-(10) to white collar workers. In column (1)-(2)-(3)-(4) and (6)-(7)-(8)-(9) we use export share on total sales to approximate firms' export activity Exp_{jt}, and the firms' total sales to approximate the term lnS_{jt}. In column (5) and (10) we use the logarithm of sales from export to approximate firms' export activity Exp_{jt}, and domestic sales to approximate the term S_{jt}. Notice that including firm-year fixed effects in the estimation makes sector-year fixed effects redundant, since firms do not change sector of activity in the estimation sample. The data source is the LIAB dataset for years 1993-2007.
*/**/*** denote significance at the 10/5/1% level respectively. Standard errors are in brackets and are clustered at firm level.

Table 3.5 – GWG and Exports: The differential Effect on Blue and White Collar Workers

	(1)	(2)	(3)	(4)	Elasticities (5)
Exp_{jt}	-0.0006	-0.0048			
	(0.005)	(0.007)			
Female * Exp_{jt}	-0.0145**	-0.0193**	-0.0120**	-0.0158**	-0.0030
	(0.007)	(0.008)	(0.006)	(0.008)	(0.002)
White Collar * Exp_{jt}	0.0117*	0.0156*	0.0135*	0.0241***	0.002
	(0.006)	(0.008)	(0.007)	(0.009)	(0.002)
Female * White Collar * Exp_{jt}	0.0273***	0.0337***	0.0280***	0.0342***	0.0082***
	(0.008)	(0.01)	(0.008)	(0.01)	(0.002)
$Ln(S_{jt})$		0.0110***			
		(0.002)			
Female * $ln(S_{jt})$		-0.0040	-0.0019	-0.0031	0.0014
		(0.003)	(0.002)	(0.002)	(0.002)
White collar * $ln(S_{jt})$		-0.0068***	-0.0050**	-0.0071**	-0.0075***
		(0.002)	(0.002)	(0.003)	(0.002)
Female * White Collar *$ln(S_{jt})$		0.0077**	0.0060**	0.0109***	-0.0018
		(0.003)	(0.003)	(0.004)	(0.002)
Experience/10	0.2518***	0.2467***	0.3784***	0.3486***	0.3493***
	(0.02)	(0.021)	(0.023)	(0.024)	(0.024)
Experience sq./100	-0.0435***	-0.0436***	-0.0443***	-0.0431***	-0.0431***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(firm size)	0.0300***	0.0234***			
	(0.004)	(0.004)			
Federal State FE	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	No	No	No
Match FE	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	No	No	Yes	Yes	Yes
Observations	8,962,723	7,737,149	7,735,686	5,646,549	5,620,203
R-sq.	0.948	0.947	0.952	0.95	0.948
Sample	All	All	All	Only Exporters	Only Exporters

Notes: The dependent variable is log wages in real values. In column (1)-(2)-(3)-(4) we use export share on total sales to approximate firms' export activity Exp_{jt}, and the firms' total sales to approximate the term lnS_{jt}. In column (5) we use the logarithm of sales from export to approximate firms' export activity Exp_{jt}, and domestic sales to approximate the term S_{jt}. Notice that including firm-year fixed effects in the estimation makes sector-year fixed effects redundant, since firms do not change sector of activity in the estimation sample. The data source is the LIAB dataset for years 1993-2007.
*/**/*** denote significance at the 10/5/1% level respectively. Standard errors are in brackets and are clustered at firm level.

Table 3.6 – Firm Demand

	Share of White Collar	Share of Female White Collar		Share of Female Blue Collar	
	(1)	(2)	(3)	(4)	(5)
Ln(Export)	-0.0011	0.0027***	0.0035***	-0.0007	-0.0005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Domestic Sales)	-0.0005	0.0028	0.0018	0.0017*	0.0006
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Female Share$_{(t-1)}$			0.8549***		0.6300***
			(0.015)		0.009
Federal State FE	Yes	Yes	Yes	Yes	Yes
Sector - Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	15,916	15,414	15,412	15,286	15,285
R-sq	0.968	0.895	0.917	0.962	0.973

Notes: The share of white collar workers in column (1) is computed as the ratio between full-time white collar workers and all full time workers. The share of female white collar workers in column (2)-(3) is computed as the ratio between full-time female white collar workers and white collar workers. The share of female blue collar workers in column (4)-(5) is computed as the ratio between full-time female blue collar workers and blue collar workers. The data source is the LIAB dataset for years 1993-2007, collapsed at the firm level.
*/**/*** denote significance at the 10/5/1% level respectively. Standard errors are in brackets and are clustered at firm level.

Table 3.7 – Hiring Patterns

Dep. Vars.:	*Ln*(1+New Hires)	New Hired White Collars	New Hired Female White Collars		New Hired Female Blue Collars	
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Export)	0.0147	0.0033	0.0041	0.0023	-0.0011	-0.0018
	(0.011)	(0.011)	(0.015)	(0.015)	(0.011)	(0.011)
Ln(Domestic Sales)	0.0420***	0.0031	0.0107	0.0111	0.0064	0.0067
	(0.016)	(0.013)	(0.018)	(0.018)	(0.013)	(0.013)
Female Share$_{(t-1)}$				-0.6331**		-0.2645
				(0.276)		(0.19)
Federal State FE	Yes	Yes	Yes	Yes	Yes	Yes
Sectory-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,916	5,844	3,627	3,627	4,256	4,256
R-sq	0.652	0.523	0.469	0.47	0.625	0.625

Notes: Newly hired workers are defined as workers employed in firm j at time y but not in $t-1$, $t-2$, $t-3$. The share of newly hired white collar workers in column (2) is computed as the ratio between newly hired full-time white collar workers and all newly hired full time workers. The share of female white collar workers in column (3)-(4) is computed as the ratio between newly hired full-time female white collar workers and newly hired white collar workers. The share of female blue collar workers in column (5)-(6) is computed as the ratio between newly hired full-time female blue collar workers and newly hired full-time blue collar workers. The data source is the LIAB dataset for years 1993-2007, collapsed at the firm level.
*/**/*** denote significance at the 10/5/1% level respectively. Standard errors are in brackets and are clustered at firm level.

Table 3.8 – Firm Demand and Export Dynamics

	Share of White Collar	Share of Female White Collar		Share of Female Blue Collar	
	(1)	(2)	(3)	(4)	(5)
Ln(Export)$_{(t-1)}$	-0.0015	0.0021	0.0021**	-0.0007	-0.0003
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Ln(Domestic Sales)$_{(t-1)}$	0.0031	-0.0020	-0.0019	-0.0013	-0.0013
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Female Share$_{(t-1)}$			0.9277***		0.6742***
			(0.019)		(0.012)
Federal State FE	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	11,367	11,049	11,049	10,966	10,966
R-sq	0.969	0.904	0.927	0.966	0.976

Notes: The share of white collar workers in column (1) is computed as the ratio between full-time white collar workers and all full time workers. The share of female white collar workers in column (2)-(3) is computed as the ratio between full-time female white collar workers and white collar workers. The share of female blue collar workers in column (4)-(5) is computed as the ratio between full-time female blue collar workers and blue collar workers. Export and domestic sales are one period lagged. The data source is the LIAB dataset for years 1993-2007, collapsed at the firm level.
*/**/*** denote significance at the 10/5/1% level respectively. Standard errors are in brackets and are clustered at firm level.

Table 3.9 – Hiring Patterns and Export Dynamics

	Ln(1+New Hires)	New Hired White Collars	New Hired Female White Collars		New Hired Female Blue Collars	
	(1)	(2)	(3)	(4)	(5)	(6)
$Ln(Export)_{(t-1)}$	-0.0010	0.0022	0.0160	0.0148	-0.0018	-0.0020
	(0.011)	(0.014)	(0.019)	(0.019)	(0.014)	(0.014)
Ln(Domestic Sales)$_{(t-1)}$	0.0063	0.0304*	-0.0153	-0.0147	-0.0119	-0.0112
	(0.016)	(0.017)	(0.022)	(0.023)	(0.017)	(0.017)
Female Share$_{(t-1)}$				-0.3183		-0.3574
				(0.395)		(0.308)
Federal State FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,367	4,175	2,524	2,524	3,020	3,020
R-sq.	0.73	0.533	0.474	0.474	0.631	0.631

Notes: Newly hired workers are defined as workers employed in firm j at time y but not in $t-1$, $t-2$, $t-3$. The share of newly hired white collar workers in column (2) is computed as the ratio between newly hired full-time white collar workers and all newly hired full time workers. The share of female white collar workers in column (3)-(4) is computed as the ratio between newly hired full-time female white collar workers and newly hired white collar workers. The share of female blue collar workers in column (5)-(6) is computed as the ratio between newly hired full-time female blue collar workers and newly hired full-time blue collar workers. Export and domestic sales are one period lagged. The data source is the LIAB dataset for years 1993-2007, collapsed at the firm level.
*/**/*** denote significance at the 10/5/1% level respectively. Standard errors are in brackets and are clustered at firm level.

Table 3.10 – Promotions

	(1)	(2)
Ln(Export)	-0.0052***	
	(0.002)	
Female**ln*(Export)	0.0021	-0.0003
	(0.002)	(0.002)
White Collar**ln*(Export)	0.0034*	0.0010
	(0.002)	(0.002)
Female*White Collar**ln*(Export)	0.0021	0.0053*
	(0.003)	(0.003)
Ln(Domestic sales)	-0.0054***	
	(0.002)	
Female**ln*(Domestic sales)	0.0024	0.0009
	(0.002)	(0.002)
White Collar**ln*(Domestic sales)	0.0036*	0.0010
	(0.002)	(0.002)
Female*White Collar* *ln*(Domestic sales)	-0.0069**	-0.0051*
	(0.003)	(0.003)
Federal State FE	Yes	Yes
Sector-Year FE	Yes	No
Match FE	Yes	Yes
Firm-Year FE	No	Yes
Observations	3,699,541	3,699,428
R-sq.	0.274	0.283

Notes: The dependent variable is probability of promotion. Promotions are identified as episodes of wage growth of workers that are 10% higher than the average wage growth of their colleagues within the firm and occupation group (white versus blue collar). The average probability of promotion in the whole dataset is equal to 5.36%. The data source is the LIAB dataset for years 1993-2007.
*/**/*** denote significance at the 10/5/1% level respectively. Standard errors are in brackets and are clustered at firm level.

Table 3.11 – Robustness Checks: Promotions

	(1)	(2)
Ln(Export)	-0.0025	
	0.001	
Female**ln*(Export)	0.0003	-0.0014
	0.001	0.001
White Collar**ln*(Export)	0.0013	0.0002
	0.001	0.001
Female*White Collar**ln*(Export)	0.0025	0.0043**
	0.002	0.002
Ln(Domestic sales)	-0.0026***	
	0.001	
Female**ln*(Domestic sales)	0.0002	0.0002
	0.001	0.001
White Collar**ln*(Domestic sales)	0.0020	0.0006
	0.001	0.001
Female*White Collar* *ln*(Domestic sales)	-0.0023	-0.0021
	0.002	0.002
Federal State FE	Yes	Yes
Sector-Year FE	Yes	No
Match FE	Yes	Yes
Firm-Year FE	No	Yes
Observations	3,699,264	3,699,148
R-sq	0.2740	0.2810

Notes: The dependent variable is probability of promotion. Promotions are identified as episodes of wage growth of workers that are 15% higher than the average wage growth of their colleagues within the firm and occupation group (white versus blue collar). The average probability of promotion in the whole dataset is equal to 2.40%. The data source is the LIAB dataset for years 1993-2007.
*/**/*** denote significance at the 10/5/1% level respectively. Standard errors are in brackets and are clustered at firm level.

Table 3.12 – Occupations by Task Content

Occupational Tasks Content (%)	**White Collar**	**Blue Collar**
Manual Routine	3.02	64.38
Manual Non Routine	5.36	8.15
Cognitive Routine	0	0.16
Analytic Non Routine	21.54	6.07
Interactive Non Routine	70.07	21.24
	100	100

Notes: The breakdown of white and blue collar occupations according to their tasks content is based on the definition of Task Intensity given in Appendix 3.B. The statistics are based on the LIAB dataset for years 1993-2007, matched to the occupation task content information obtained from the “Survey on qualification and working conditions”.

Table 3.13 – Export and Gender Wage Gap by Task Intensity: White Collar, Analytic and Interactive Jobs

White Collar:	**Analytic Non Routine**				**Interactive Non Routine**			
				Elasticities				Elasticities
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exp_{jt}	0.00145	-0.00476			0.00153	-0.00022		
	0.004	0.004			0.003	0.003		
Female* Exp_{jt}	0.0057	0.0081	0.0055	0.0004	0.0071**	0.0067*	0.0058	0.0032***
	0.005	0.008	0.008	0.002	0.003	0.004	0.004	0.001
$Ln(S_{jt})$		0.0024**				0.0033***		
		0.001				0.001		
Female *$ln(S_{jt})$		0.0011	-0.0007	0.0005		0.0055***	0.0044**	0.0024
		0.002	0.002	0.002		0.002	0.002	0.002
Ln(firm size)	0.0089***	0.0078***			0.0146***	0.0127***		
	0.003	0.003			0.002	0.003		
Federal State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	No	No	Yes	Yes	No	No
Match FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	631,130	569,444	568,494	428,580	1,828,040	1,521,720	1,516,515	960,278
R-sq	0.962	0.962	0.964	0.962	0.962	0.96	0.963	0.951
Sample	All	All	All	Only Exporters	All	All	All	Only Exporters

Notes: The dependent variable is log wages in real values. Column (1)-(2)-(3)-(4) refers to the sub-sample of workers employed in white collar, analytic non-routine occupations, while columns (5)-(6)-(7)-(8) refers to workers employed in white collar interactive non-routine occupations. In columns (1)-(2)-(3)-(5)-(6)-(7) we use export share on total sales to approximate firms' export activity Exp_{jt}, and the firms' total sales to approximate the term lnS_{jt}. In columns (4) and (8) we use the logarithm of sales from export to approximate firms' export activity Exp_{jt}, and the logarithm of domestic sales to approximate the term lnS_{jt}. Other sets of controls include experience and experience squared. The data source is the LIAB dataset for years 1993-2007, combined with the Survey on qualification and working conditions by occupation code (Kldb2010) at 3 digit level of detail.
*/**/*** denote significance at the 10/5/1% level respectively. Standard errors are in brackets and are clustered at firm level.

Table 3.14 – Export and Gender Wage Gap by Task Intensity: Blue Collar, Manual and Interactive Jobs

Blue Collar:	**Manual Routine**				**Manual Non-Routine**				**Interactive Non Routine**			
				Elasticities				Elasticities				Elasticities
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Exp_{jt}	0.00387	0.00188			0.01043	0.00812			0.00188	0.00045		
	0.006	0.007			0.01	0.009			0.005	0.006		
Female* Exp_{jt}	-0.0204**	-0.0224**	-0.0130*	-0.0029	-0.0119	-0.0243**	-0.0125	0.0023	-0.0004	-0.0129	-0.0077	0.0013
	0.008	0.009	0.007	0.002	0.01	0.01	0.011	0.003	0.005	0.009	0.006	0.002
$Ln(S_{jt})$		0.0090***				-0.0001				0.0069**		
		0.002				0.003				0.003		
Female * $ln(S_{jt})$		-0.0051*	-0.0022	0.0027		0.0058	0.0010	0.0061		0.0096	0.0091*	0.0063**
		0.003	0.002	0.002		0.005	0.005	(0.006)		0.006	0.005	0.003
Ln(firm size)	0.0475***	0.0404***			0.0350***	0.0328***			0.0392***	0.0323***		
	0.005	0.005			0.006	0.007			0.01	0.008		
Observations	4,167,086	3,619,521	3,616,644	2,752,094	374,669	329,727	326,195	205,853	1,207,781	1,020,565	1,015,909	710,474
R-sq.	0.922	0.92	0.932	0.929	0.965	0.963	0.968	0.947	0.959	0.959	0.964	0.953
Federal State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Match FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Sample	All	All	All	Only Exporters	All	All	All	Only Exporters	All	All	All	Only Exporters

Notes: The dependent variable is log wages in real values. Column (1)-(2)-(3)-(4) refers to the sub-sample of workers employed in blue collar, manual routine occupations, while columns (5)-(6)-(7)-(8) refers to workers employed in blue collar manual non-routine occupation and columns (9)-(10)-(11)-(12) refers to workers employed in blue collar interactive non-routine occupations. In columns (1)-(2)-(3)-(5)-(6)-(7)-(9)-(10)-(11) we use export share on total sales to approximate firms' export activity Exp_{jt}, and the firms' total sales to approximate the term lnS_{jt}. In columns (4)-(8)-(12) we use the logarithm of sales from export to approximate firms' export activity Exp_{jt}, and the logarithm of domestic sales to approximate the term lnS_{jt}. Other sets of controls include experience and experience squared. The data source is the LIAB dataset for years 1993-2007, combined with the Survey on qualification and working conditions by occupation code (Kldb2010) at 3 digit level of detail.
*/**/*** denote significance at the 10/5/1% level respectively. Standard errors are in brackets and are clustered at firm level.

Table 3.15 – Robustness Checks: Wage Censoring

	(1)	(2)	(3)	Elasticity (4)
Exp_{jt}	0.0073			
	(0.003)			
Female * Exp_{jt}	0.0081**	0.0069*	0.0124*	0.0051**
	(0.004)	(0.004)	(0.007)	(0.002)
Censored wage at $(t-1)$	0.0174***	0.0133***	0.0195***	0.0224*
	(0.002)	(0.002)	(0.003)	(0.012)
Female * Censored wage at $(t-1)$	0.0009	0.0027	0.0075*	0.0154
	(0.003)	(0.003)	(0.004)	(0.021)
Censored wage at $(t-1)$ * Exp_{jt}	-0.0226***	-0.0176***	-0.0283***	-0.0048***
	(0.004)	(0.003)	0.005	(0.001)
Female * Censored wage at $(t-1)$ * Exp_{jt}	0.0134**	0.0107**	0.0049	0.0017*
	(0.006)	(0.005)	(0.006)	(0.001)
Female * S_{jt}				0.0016
				(0.002)
Censored wage at $(t-1)$ * S_{jt}				0.0039***
				(0.001)
Female * Censored wage at $(t-1)$				-0.0019*
				(0.001)
Experience/10	0.3523***	0.5008***	0.4475***	0.4397***
	(0.035)	(0.051)	(0.059)	(0.058)
Experience sq./100	-0.0480***	-0.0482***	-0.0501***	-0.0500***
	(0.002)	(0.002)	(0.004)	(0.004)
Ln(Firm size)	0.0117			
	0.002			
Federal State FE	Yes	No	No	No
Sector-Year FE	Yes	No	No	No
Match FE	Yes	Yes	Yes	Yes
Firm-Year FE	No	Yes	Yes	Yes
Observations	1,583,254	1,578,584	983,636	916,983
R-sq	0.961	0.964	0.954	0.955
Sample	White Collars All	White Collars All	White Collars Only Exporters	White Collars Only Exporters

Notes: The results are obtained from estimating model (3.4) on sub-sample of white collar workers only in the LIAB dataset for years 1993-2007 buy replacing the variable white collar with censored wages at time $t-1$. The dependent variable is log wages in real values. In Column (1)-(2)-(3) we use export share on total sales to approximate firms' export activity Exp_{jt},. In Column (4) we use the logarithm of sales from export to approximate firms' export activity Exp_{jt}, and the logarithm of domestic sales to approximate the term lnS_{jt}.
*/**/*** denote significance at the 10/5/1% level respectively. Standard errors are in brackets and are clustered at firm level.

Table 3.16 – Robustness Checks: Gender Wage Gap and Export Dynamics

			Elasticities
	(1)	(2)	(3)
Exp_{t-1}	-0.0121		
	(0.008)		
Female * Exp_{t-1}	-0.0070	-0.0095	-0.0024
	(0.009)	(0.008)	(0.002)
White Collar * Exp_{t-1}	0.0186**	0.0164**	0.0027
	(0.009)	(0.008)	(0.002)
Female * White Collar *Exp_{t-1}	0.0252**	0.0252***	0.0084***
	(0.01)	(0.009)	(0.002)
S_{t-1}	0.0065**		
	(0.003)		
Female * S_{t-1}	-0.0053*	-0.0027	0.0005
	(0.003)	(0.002)	(0.002)
White Collar * S_{t-1}	-0.0029	-0.0018	-0.0046**
	(0.003)	(0.002)	(0.002)
Female * White Collar * S_{t-1}	0.0094**	0.0065**	-0.0033*
	(0.004)	(0.003)	(0.002)
Federal State FE	Yes	No	No
Industry-Year FE	Yes	No	No
Match FE	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes
Observations	5,022,162	5,021,014	3,736,806
R-sq.	0.949	0.954	0.952
Sample	All	All	Only Exporters

Notes: The results are obtained from estimating model (3.4) on the LIAB dataset for years 1993-2007. The dependent variable is log wages in real values. In Column (1)-(2)we use export share on total sales to approximate firms' export activity $Exp_{j,t-1}$,. In Column (3) we use the logarithm of sales from export to approximate firms' export activity $Exp_{j,t-1}$, and the logarithm of domestic sales to approximate the term $lnS_{j,t-1}$. Controls for experience, experience squared and (log of) firm size are also included.
*/**/*** denote significance at the 10/5/1% level respectively. Standard errors are in brackets and are clustered at firm level.

Table 3.17 – Robustness Checks: Gender Wage Gap and Export for High Tenure Workers

	(1)	(2)	Elasticities (3)
Exp_t	-0.0049		
	(0.007)		
Female* Exp_t	-0.0185**	-0.0099	-0.0024
	(0.008)	(0.007)	(0.002)
White Collar * Exp_t	0.0122	0.0103	0.0001
	(0.009)	(0.008)	(0.002)
Female* White Collar * Exp_t	0.0349***	0.0295***	0.0088***
	(0.01)	(0.009)	(0.002)
S_t	0.0118***		
	(0.002)		
Female * S_t	-0.0051*	-0.0022	0.0005
	(0.003)	(0.002)	(0.002)
White Collar * S_t	-0.0091***	-0.0075**	-0.0080***
	(0.002)	(0.003)	(0.003)
Female * White Collar * S_t	0.0106***	0.0087***	-0.0006
	(0.003)	(0.003)	(0.002)
Federal State FE	Yes	No	No
Industry-Year FE	Yes	No	No
Match FE	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes
Observations	6,325,589	6,323,303	4,708,571
R-sq.	0.946	0.952	0.95

Notes: The results are obtained from estimating model (3.4) on the sub-sample of high-tenure workers only in the LIAB dataset for years 1993-2000. The dependent variable is log wages in real values. In Column (1)-(2)we use export share on total sales to approximate firms' export activity $Exp_{j,}$. In Column (3) we use the logarithm of sales from export to approximate firms' export activity Exp_j, and the logarithm of domestic sales to approximate the term $lnS_{j,t}$. Controls for experience, experience squared and (log of) firm size are also included.
*/**/*** denote significance at the 10/5/1% level respectively. Standard errors are in brackets and are clustered at firm level.

Appendix

3.A Classification of Sectors of Activity

Table 3.A.1 – Sector of Activity (NACE Rev. 2)

	Description
10	Manufacture of food products
11	Manufacture of beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork, except furniture manufacture of articles of straw and plaiting materials
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c.
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing
33	Repair and installation of machinery and equipment
35	Electricity, gas, steam and air conditioning supply
36	Water collection, treatment and supply
37	Sewerage
38	Waste collection, treatment and disposal activities; materials recovery
39	Remediation activities and other waste management services
41	Construction of buildings
42	Civil engineering
43	Specialised construction activities
45	Wholesale and retail trade and repair of motor vehicles and motorcycles

46	Wholesale trade, except of motor vehicles and motorcycles
47	Retail trade, except of motor vehicles and motorcycles
49	Land transport and transport via pipelines
50	Water transport
51	Air transport
52	Warehousing and support activities for transportation
55	Accommodation
56	Food and beverage service activities
58	Publishing activities
59	Motion picture, video and television programme production, sound recording and music publishing activities
60	Programming and broadcasting activities
61	Telecommunications
62	Computer programming, consultancy and related activities
63	Information service activities
64	Financial service activities, except insurance and pension funding
65	Insurance, reinsurance and pension funding, except compulsory social security
66	Activities auxiliary to financial services and insurance activities
68	Real estate activities
69	Legal and accounting activities
70	Activities of head offices; management consultancy activities
71	Architectural and engineering activities; technical testing and analysis
72	Scientific research and development
73	Advertising and market research
74	Other professional, scientific and technical activities
75	Veterinary activities
77	Rental and leasing activities
78	Employment activities
79	Travel agency, tour operator and other reservation service and related activities
80	Security and investigation activities
81	Services to buildings and landscape activities
82	Office administrative, office support and other business support activities
84	Public administration and defence; compulsory social security
85	Education
86	Human health activities
87	Residential care activities
88	Social work activities without accommodation
90	Creative, arts and entertainment activities
91	Libraries, archives, museums and other cultural activities
92	Gambling and betting activities
93	Sports activities and amusement and recreation activities
94	Activities of membership organisations
95	Repair of computers and personal and household goods
96	Other personal service activities
97	Activities of households as employers of domestic personnel
98	Undifferentiated goods- and services-producing activities of private households for own us
99	Activities of extraterritorial organisations and bodies

3.B Task Content of Occupations

The second source of information used in our analysis, in addition to LIAB, is the "Survey on qualification and working conditions" carried out by the German Federal Institute for Vocational Training (BIBB) and the Research Institute of the Federal Employment Service (IAB). The dataset consists of a repeated cross section of a random sample of workers covering 0.1 percent of the German labour force. It was conducted in 1979, 1986, 1992, 1999, 2006 and 2012 and we use it to classify occupations into groups according to their tasks' content.

The detailed information on tasks performed in each job allows us to classify 15 longitudinally consistent tasks relating to what the worker does on the job following the methodology given in Becker and Muendler (2014). Once the tasks are correctly defined, each occupation is classified according to the following five categories defined by Spitz-Oener (2006), based on the intensity of activity performed on the job: 1) Manual-routine, 2) Manual non-routine, 3) Cognitive routine, 4) Analytic non-routine, 5) Interactive non-routine. The correspondence between occupation category and task is reported in Table 3.B1.

We follow Antonczyk, Fitzenberger, and Leuschner (2009) and define the steps to classify each occupation by its task intensity as follows. First, we define a certain level of intensity of performance of activities belonging to task category c for individual i (employed in occupation k) at time t, by taking the ratio between the sum of all the activities performed by i that belong to category c and the sum of all activities performed by i across all categories. This represents an indicator of the intensity of activities performed by i in category c, and formally is defined as following:

$$\text{Intensity Index}^{c}_{ikt} = \frac{\sum_a (\text{tasks a in category c})_{ikt}}{\sum_a (\text{all tasks a})_{ikt}}$$

Then, to obtain a measure of the intensity with which a certain category of tasks is performed within each occupation, we just average the Intensity Index$^{c}_{ikt}$ across all individuals employed in occupation k. Formally, we obtain the following index:

$$\text{Task Index}_{\,c,k,t} = \frac{\sum_i \text{Task Index}^{c}_{ikt}}{N_k}$$

Finally, we consider occupation k to belong to category c if the maximum value of Task Index $_{c,k,t}$ across all categories is attached to category c.

In Table 3.B2 we provide an example of the values of the Task Indices defined above, Task Index $_{c,k,t}$, for two occupations, teacher and baker. We can see that in each year of the survey teacher belongs the interactive non-routine category and baker to manual routine. We can also notice that within strongly manual routine occupations, like baker, there is a substantial reduction of intensity of manual routine tasks throughout time, indicating the role of automation (see for example Cortes, Jaimovich, and Siu (2018)).

Table 3.B.1 – Tasks and Occupation Classification

Category	Task
Manual Routine	Manufacture, Produce Goods
	Transport, Store, Dispatch
	Oversee, Control Machinery and Techn. Processes
Manual Non Routine	Repair, Maintain
	Entertain, Accommodate, Prepare Foods
	Nurse, Look After, Cure
Cognitive Routine	Measure, Inspect, Control Quality
Analytical Non Routine	Gather Information, Develop, Research, Construct
	Program a Computer
	Apply Legal Knowledge
Interactive Non Routine	Purchase, Procure, Sell
	Advertise, Promote, Conduct Marketing and PR
	Organize, Plan, Prepare (others' work)
	Consult and Inform
	Train, Teach, Instruct, Educate

Table 3.B.2 – Tasks and Occupation Classification

Task Index $_{c,k,t}$	Teacher			Baker		
	1992	**1999**	**2006**	**1992**	**1999**	**2006**
Manual routine	0.02	0.02	0.07	**0.73**	**0.37**	**0.31**
Manual non-routine	0.01	0.22	0.14	0.03	0.16	0.13
Cognitive routine	0.04	0.07	0.08	0.01	0.11	0.12
Analytical non-routine	0.11	0.15	0.24	0.05	0.04	0.13
Interactive non-routine	**0.82**	**0.54**	**0.47**	0.19	0.31	0.30

3.C Export and Gender Wage Gap: Additional Specifications

In the main body of this paper we have shown that an increase in firms' export activity does not have any significant effect on the gender wage gap in total, but that it is associated to a significant increase in relative wages of female white collar workers and to a significant decrease in relative wages of female blue collar workers.

These results are obtained exploiting *within firms* and *within worker-firm matches* variation of export and relative wages. We mainly focus on this level of detail because we want to capture the (closest to the) true causal relationship between these two variables. We believe that only looking at changes in the relative wages of a specific male-female pair of workers employed by the same firm as it increases its export activity eliminates important sources of bias related to firm heterogeneity in productivity or hiring process and workers' heterogeneity in innate ability.

However, to the best of our knowledge, most of the existing literature, with the exception of Bøler, Javorcik, and Ulltveit-Moe (2018), uses sector and firm-level data, which only allows to exploit sector and firm level variation to investigate the relationship between export and gender wage gap. For example, Black and Brainerd (2004) and Saure and Zoabi (2014), using sector level data on the US, find contrasting results on the role of international trade in the gender wage gap. In Black and Brainerd (2004) trade liberalization is interpreted as an increase in competition on the labour market which, under the assumption that firms operate in a non competitive market and adopt a costly discriminatory behaviour against female workers, leads to a reduction in the gender wage gap. On the contrary, Saure and Zoabi (2014) show that trade liberalization widens the gender wage gap. They motivate their findings by modelling the labour market under the assumption of a strong complementarity between female labour and capital intensive technology. After a trade shock, the capital sector expands, attracting male workers from the labour intensive sector, thereby reducing the capital-labour ratio and increasing the gender wage gap. Additionally, Ozler (2000), exploiting firm level data on Turkey, finds a positive correlation between firm level demand for female workers and export activity. Ederington, Minier, and Troske (2009) further confirms that the demand for female workers increases in firms that operate in industries that experience more relevant tariff reductions in Colombia. Finally, Juhn, Ujhelyi, and Villegas-Sanchez (2014) show that women in blue collar occupations in Mexico experience an increase in their relative wages after a cut in tariffs, while white collar women remain largely unaffected by such policy.

To be able to compare our results to the existing literature, in this section we estimate the relation between export and gender wage gap exploiting only within-sector and within-firm source of variation in the data. Specifically, we estimate on the whole sample and then on the sub-samples of blue and white collar workers the following linear regression models:

$$\ln w_{ijst} = \beta_0 fem_i + \beta_1 Exp_{jt} + \beta_2 fem_i * Exp_{jt} + \mathbf{C}'_{it}\pi_1 + \mathbf{F}'_{jt}\pi_2 + \varepsilon_{ijst} \qquad (3.8)$$

$$\ln w_{ijst} = \beta_0 fem_i + \beta_1 Exp_{jt} + \beta_2 fem_i * Exp_{jt} + \mathbf{C}'_{it}\pi_1 + \mathbf{F}'_{jt}\pi_2 + \eta_{st} + \varepsilon_{ijst} \tag{3.9}$$

$$\ln w_{ijst} = \beta_0 fem_i + \beta_1 Exp_{jt} + \beta_2 fem_i * Exp_{jt} + \mathbf{C}'_{it}\pi_1 + \mathbf{F}'_{jt}\pi_2 + \eta_{st} + \eta_j + \varepsilon_{ijst} \tag{3.10}$$

where, w_{ijst} represents the wage of individual i in firm j in sector s at time t; fem_i is a dummy variable equal to 1 if the worker is a woman and Exp_{jt} represents the share of exports on total sales of firm j at time t. Matrix $\mathbf{C}_{it}$ contains vectors of individual characteristics of individual i at time t, such as education, experience and its square, a dummy variable for white collar and German citizenship. Matrix $\mathbf{F}_{jt}$ contains a vector of firms' characteristics, like the (log of) the number of firms' employees, and fixed effects for the federal state in which the establishment is located. Specification (3.9) further includes a set of fixed effects for sector-year denoted as η_{st} and in specification (3.10) we add firm fixed effects η_j.

The results of the estimation of the three models for the whole sample are reported in Table 3.C1, respectively in column (1), (2) and (3).

The estimation of specification (3.8) shows that women are paid on average 25% less than men, and that firms that export more pay their male employees higher wages and are characterised by a lower gender wage gap.

This specification compares the size of the gender wage gaps in firms with different export shares that operate in different sectors of activity. The estimation of the correlation between the gender wage gap and export is then likely to be biased by sector-level heterogeneity. For example, if export-oriented firms are concentrated in sectors that systematically employ more female workers, it will also reflect the difference in the gender composition of the workforce in addition to the true effect of export.

This possible source of bias is taken into account in specification (3.9), in which sector-year fixed effects are included. In this case, the estimation of the gender wage gap exploits within sector (and year) variation of firms' export activity. Specifically, it allows us to compare the gender wage gap of different firms with different export shares that operate within the same sector of activity.

The results of this specification are reported in column (2) and show that being employed in a firm that has a 1 percentage point higher export share is associated to a 0.028% increase in salary for male workers, and to a 0.09% reduction in the gender wage gap. If we compare this result to the one in column (1) we notice that the relative female-male wage response to an increase in export is lower when we control for sector-year fixed effects, confirming the (upward) bias in the coefficient estimated in the first specification.

The results of model (3.10), in which we add firm fixed effects to the baseline specification, are reported in column (3), and confirm the estimation results of model (3.8) and (3.9), showing a negative correlation between export and gender wage gap. The coefficient of interest, $\hat{\beta}_2$, in this case is smaller than in specification (3.9), indicating an additional source of bias, possibly due to the different gender workforce composition between firms within sectors.

The estimation results for the sub-samples of blue collar (columns (1)-(2)-(3))

and white collar (columns (4)-(5)-(6)) workers are reported in Table 3.C2. It is interesting to notice that, in contrast with the results we found in the main text, when exploiting only within sector and within firm source of variation in the data, both blue collar and white collar female workers see their relative wages increase in conjunction with a rise in firms' export.

These results confirm what was found in previous papers (e.g. Juhn, Ujhelyi, and Villegas-Sanchez (2014)) but also, when compared to the results obtained in this work using the main identification strategy that exploits within match source of variation, indicate the key importance of workers' characteristics in driving the results. When these characteristics are taken into account, the correlation between relative female-male workers' wages and export is in fact much smaller and becomes negative in the case of blue collar workers (see Table 3.4). This result provides some evidence for the assortative matching theory, which states that firms select higher ability workers as they intensify export and pay them higher wages (Helpman, Itskhoki, and Redding, 2010).

Table 3.C.1 – Export Share and Gender Wage Gap: Other Specifications

	(1)	(2)	(3)
Female	-0.2588***	-0.2333***	-0.2037***
	(0.006)	(0.005)	(0.003)
Export Share	0.0967***	0.0285***	-0.0085*
	(0.012)	(0.009)	(0.005)
Female * Export Share	0.1390***	0.0928***	0.0616***
	(0.014)	(0.013)	(0.01)
Experience/10	0.2337***	0.2380***	0.2182***
	(0.005)	(0.004)	(0.004)
Experience sq./100	-0.0412***	-0.0446***	-0.0411***
	(0.002)	(0.001)	(0.001)
White Collar	0.1734***	0.1805***	0.1603***
	(0.004)	(0.004)	(0.003)
German	0.0245***	0.0188***	0.0233***
	(0.003)	(0.002)	(0.001)
Medium Skill	0.1333***	0.1217***	0.1060***
	(0.004)	(0.003)	(0.002)
High Skill	0.3507***	0.3239***	0.2842***
	(0.007)	(0.006)	(0.005)
Log (Firm Size)	0.0439***	0.0363***	-0.0013
	(0.002)	(0.002)	(0.004)
Federal State FE	Yes	Yes	Yes
Industry-Year FE	No	Yes	Yes
Firm FE	No	No	Yes
Observations	10,560,478	10,560,478	10,560,198
R-sq	0.479	0.524	0.634

Notes: The dependent variable is log wages in real values. The variable Exp_{jt} represents the firms' export share (relative to total sales). The variable $Ln(S_{jt})$ represents the (log of) the firms' total sales. The data source is the LIAB dataset for years 1993-2007.
*/**/*** denote significance at the 10/5/1% level respectively. Standard errors are in brackets and are clustered at firm level.

Table 3.C.2 – Export Share and Gender Wage Gap for Blue and White Collar Workers: Other Specifications

	Blue Collar			**White Collar**		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.2826***	-0.2455***	-0.1911***	-0.2413***	-0.2253***	-0.1996***
	(0.009)	(0.007)	(0.004)	(0.006)	(0.005)	(0.004)
Export Share	0.0970***	0.0350***	-0.0024	0.0891***	-0.0010	-0.0122**
	(0.013)	(0.01)	(0.006)	(0.015)	(0.011)	(0.005)
Female * Export Share	0.1609***	0.0963***	0.0429***	0.1520***	0.1146***	0.0548***
	(0.022)	(0.018)	(0.01)	(0.017)	(0.016)	(0.016)
Experience/10	0.2142***	0.2132***	0.1945***	0.2829***	0.2892***	0.2699***
	(0.006)	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)
Experience sq./100	-0.0359***	-0.0381***	-0.0356***	-0.0545***	-0.0580***	-0.0533***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
German	0.0236***	0.0185***	0.0238***	0.0148**	-0.0004	-0.0018
	(0.003)	(0.002)	(0.002)	(0.006)	(0.004)	(0.003)
Medium Skill	0.1410***	0.1244***	0.1034***	0.0653***	0.0652***	0.0710***
	(0.004)	(0.003)	(0.002)	(0.008)	(0.007)	(0.006)
High Skill	0.4163***	0.3950***	0.3418***	0.2884***	0.2635***	0.2433***
	(0.008)	(0.007)	(0.006)	(0.011)	(0.009)	(0.008)
Ln(Firm Size)	0.0462***	0.0363***	0.0077	0.0389***	0.0397***	-0.0074**
	(0.003)	(0.002)	(0.005)	(0.002)	(0.002)	(0.003)
Federal State FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	No	Yes	Yes	No	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes
Observations	7,245,763	7,245,757	7,245,195	3,314,715	3,314,707	3,313,860
R-sq.	0.415	0.482	0.616	0.472	0.516	0.627

Notes: The dependent variable is log wages in real values. The results reported in columns (1)-(2)-(3) refer to blue collar workers and in columns (4)-(5)-(6) to white collar workers. The data source is the LIAB dataset for years 1993-2007.
*/**/*** denote significance at the 10/5/1% level respectively. Standard errors are in brackets and are clustered at firm level.

References

Amiti, Mary and Donald Davis (2012). “Trade, Firms, and Wages: Theory and Evidence”. In: *Review of Economic Studies* 79.1, pp. 1–36.

Antonczyk, Dirk, Bernd Fitzenberger, and Ute Leuschner (2009). *Can a Task-Based Approach Explain the Recent Changes in the German Wage Structure?* ZEW Discussion Papers 08-132. ZEW - Leibniz Centre for European Economic Research.

Baumgarten, Daniel, Ingo Geishecker, and Holger Görg (2013). “Offshoring, tasks, and the skill-wage pattern”. In: *European Economic Review* 61.C, pp. 132–152.

Becker, Sascha O., Karolina Ekholm, and Marc-Andreas Muendler (2013). “Offshoring and the onshore composition of tasks and skills”. In: *Journal of International Economics* 90.1, pp. 91–106.

Becker, Sascha O. and Marc-Andreas Muendler (2014). *Trade and Tasks: An Exploration over Three Decades in Germany.* CESifo Working Paper Series 5122. CESifo Group Munich.

Bernard, Andrew B., J. Bradford Jensen, Stephen J. Redding, and Peter K. Schott (2007). “Firms in International Trade”. In: *Journal of Economic Perspectives* 21.3, pp. 105–130.

Black, Sandra and Elizabeth Brainerd (2004). “Importing Equality? The Impact of Globalization on Gender Discrimination”. In: *ILR Review* 57.4, pp. 540–559.

Black, Sandra E. and Alexandra Spitz-Oener (2010). “Explaining Women’s Success: Technological Change and the Skill Content of Women’s Work”. In: *The Review of Economics and Statistics* 92.1, pp. 187–194.

Bøler, Esther Ann, Beata Javorcik, and Karen Helene Ulltveit-Moe (2018). “Working across time zones: Exporters and the gender wage gap”. In: *Journal of International Economics* 111.C, pp. 122–133.

Bonfiglioli, Alessandra, Rosario Crinò, and Gino Gancia (2018). “Betting on Exports: Trade and Endogenous Heterogeneity”. In: *Economic Journal* 128.609, pp. 612–651.

— (2019). *Firms and Economic Performance: A View from Trade.* CEPR Discussion Papers 12829.

Borghans, Lex, Bas Ter Weel, and Bruce A. Weinberg (2014). “People Skills and the Labor-Market Outcomes of Underrepresented Groups”. In: *ILR Review* 67.2, pp. 287–334.

Bronson, Mary Ann and Peter Skogman Thoursie (2017). *The Lifecycle Wage Growth of Men and Women: Explaining Gender Differences in Wage Trajectories.* Working Papers gueconwpa 17-17-06. Georgetown University, Department of Economics.

Card, David, Ana Rute Cardoso, and Patrick Kline (2015). “ Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women *”. In: *The Quarterly Journal of Economics* 131.2, pp. 633–686.

Cortes, Guido Matias, Nir Jaimovich, and Henry E Siu (2018). *The End of Men and Rise of Women in the High-Skilled Labor Market.* Working Paper 24274. National Bureau of Economic Research.

Ederington, Josh, Jenny Minier, and Kenneth Troske (2009). *Where the Girls Are: Trade and Labor Market Segregation in Colombia.* IZA Discussion Papers 4131. Institute of Labor Economics (IZA).

Epifani, Paolo and Gino Gancia (2008). “The Skill Bias of World Trade*”. In: *The Economic Journal* 118.530, pp. 927–960.

Goldin, Claudia (2014). “A Grand Gender Convergence: Its Last Chapter”. In: *American Economic Review* 104.4, pp. 1091–1119.

Helpman, Elhanan (2018). *Globalization and Inequality*. Cambridge: Harvard University Press.

Helpman, Elhanan, Oleg Itskhoki, and Stephen Redding (2010). “Inequality and Unemployment in a Global Economy”. In: *Econometrica* 78.4, pp. 1239–1283.

Juhn, Chinhui, Gergely Ujhelyi, and Carolina Villegas-Sanchez (2014). “Men, women, and machines: How trade impacts gender inequality”. In: *Journal of Development Economics* 106.C, pp. 179–193.

Ngai, L. Rachel and Barbara Petrongolo (2017). “Gender Gaps and the Rise of the Service Economy”. In: *American Economic Journal: Macroeconomics* 9.4, pp. 1–44.

Olivetti, Claudia and Barbara Petrongolo (2016). “The Evolution of Gender Gaps in Industrialized Countries”. In: *Annual Review of Economics* 8.1, pp. 405–434.

Ozler, Sule (2000). “Export Orientation and Female Share of Employment: Evidence from Turkey”. In: *World Development* 28.7, pp. 1239–1248.

Sauré, Philip and Hosny Zoabi (2014). “International trade, the gender wage gap and female labor force participation”. In: *Journal of Development Economics* 111.C, pp. 17–33.

Saure, Philip and Hosny Zoabi (2014). “International trade, the gender wage gap and female labor force participation”. In: *Journal of Development Economics* 111.3, pp. 17–33.

Schank, Thorsten, Claus Schnabel, and Joachim Wagner (2007). “Do exporters really pay higher wages? First evidence from German linked employer-employee data”. In: *Journal of International Economics* 72.1, pp. 52–74.

Spitz-Oener, Alexandra (2006). “Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure”. In: *Journal of Labor Economics* 24.2, pp. 235–270.

Stolper, Wolfgang F. and Paul A. Samuelson (1941). “Protection and Real Wages”. In: *The Review of Economic Studies* 9.1, pp. 58–73.